Deep Reinforcement Learning

2024-25 Second Semester, M.Tech (AIML)

Session #3-4-5:
Markov Decision Processes , Dynamic Programming Solutions

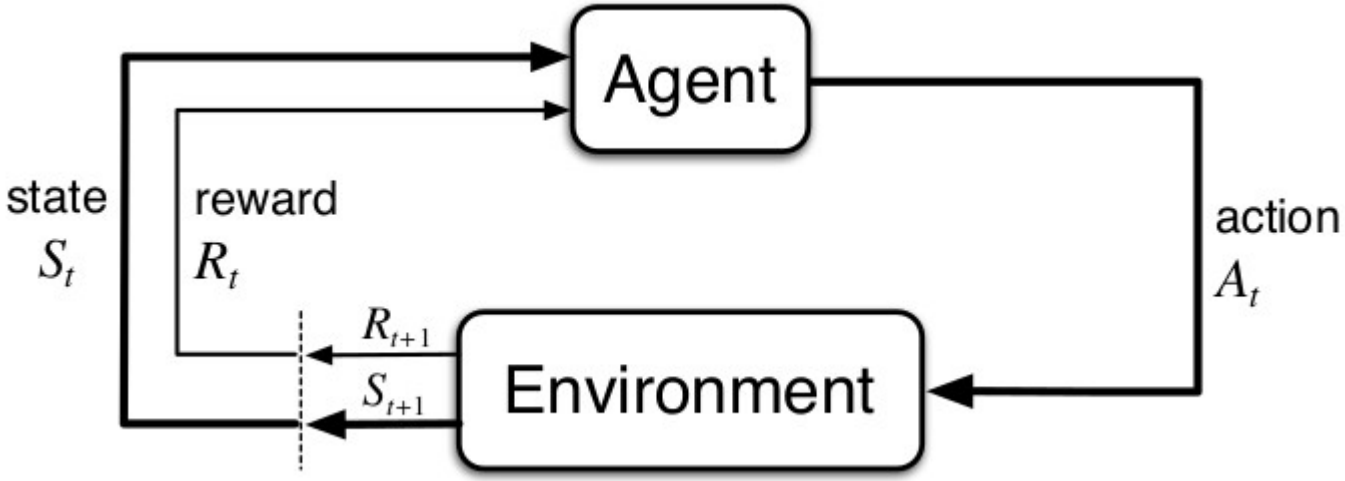
Agenda for the class

- Agent-Environment Interface (Sequential Decision Problem)
- MDP
  - Defining MDP,
  - Rewards,
  - Returns, Policy & Value Function,
  - Optimal Policy and Value Functions
- Approaches to solve MDP

Acknowledgements: Some of the slides were adopted *with permission* from the course CSCE-689 (Texas A&M University) by Prof. Guni Sharon

Agent-Environment Interface

- Agent - Learner & the decision maker
- Environment - Everything outside the agent
- Interaction:
  - Agent performs an action
  - Environment responds by
    - presenting a new situation (change in state)
    - presents numerical reward
- Objective (of the interaction):
  - Maximize the return (cumulative rewards) over time



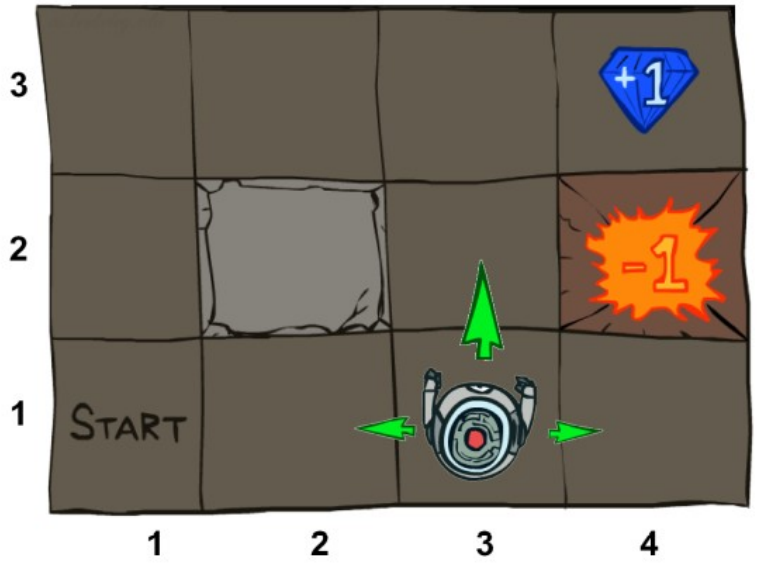
Note:

- Interaction occurs in discrete time steps

$$S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3, \ldots$$

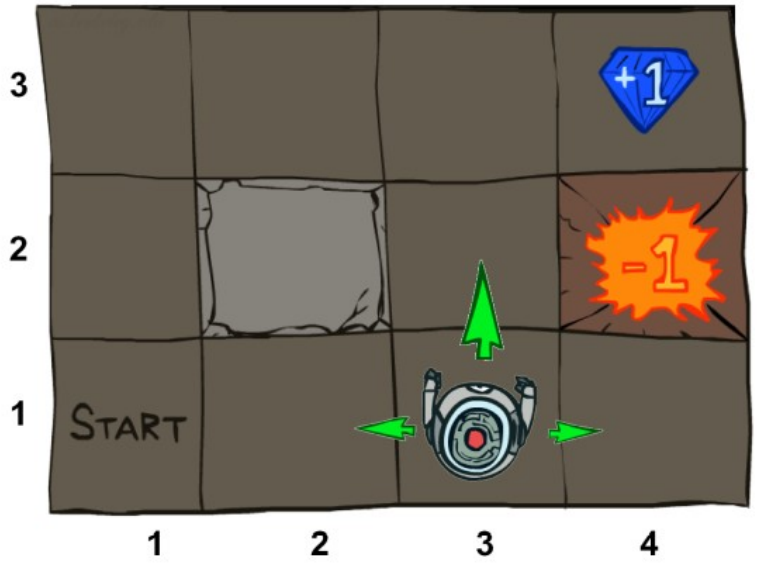
Grid World Example

- A maze-like problem
  - The agent lives in a grid
  - Walls block the agent's path
- Noisy movement: actions do not always go as planned
  - 80% of the time, the action North takes the agent North (if there is no wall there)
  - 10% of the time, North takes the agent West; 10% East
  - If there is a wall in the direction the agent would have been taken, the agent stays put
- The agent receives rewards each time step
  - -0.1 per step (battery loss)
  - +1 if arriving at (4,3) ; -1 for arriving at (4,2) ;1 for arriving at (2,2)
- Goal: maximize accumulated rewards



Markov Decision Processes

- An MDP is defined by
  - A set of states
  - A set of actions
  - State-transition probabilities
    - Probability of arriving to after performing at
    - Also called the model dynamics
  - A reward function
    - The utility gained from arriving to after performing at
    - Sometimes just or even
  - A start state
  - Maybe a terminal state



Markov Decision Processes

Model Dynamics

$$p(s', r \mid s, a) \doteq \Pr\{S_t = s', R_t = r \mid S_{t-1} = s, A_{t-1} = a\}$$

State-transition probabilities

$$p(s' \mid s, a) \doteq \Pr\{S_t = s' \mid S_{t-1} = s, A_{t-1} = a\} = \sum_{r \in \mathcal{R}} p(s', r \mid s, a)$$

Expected rewards for state–action–next-state triples

$$r(s, a, s') \doteq \mathbb{E}[R_t \mid S_{t-1} = s, A_{t-1} = a, S_t = s'] = \sum_{r \in \mathcal{R}} r \frac{p(s', r \mid s, a)}{p(s' \mid s, a)}$$

Markov Decision Processes - Discussion

- *MDP framework is abstract and flexible*
  - Time steps need not refer to fixed intervals of real time
  - The actions can be
    - at low-level controls or high-level decisions
    - totally mental or computational
  - States can take a wide variety of forms
    - Determined by *low-level sensations* or *high-level and abstract* (ex. symbolic descriptions of objects in a room)
- *The agent–environment boundary represents the limit of the agent's absolute control*, not of its knowledge.
  - *The boundary can be located at different places for different purposes*

Markov Decision Processes - Discussion

- *MDP framework is a considerable abstraction of the problem of goal-directed learning from interaction.*
- It proposes that *whatever the details of the sensory, memory, and control apparatus, and whatever objective one is trying to achieve, any problem of learning goal-directed behavior can be reduced to three signals passing back and forth between an agent and its environment:*
  - *one signal to represent the choices made by the agent (the actions)*
  - *one signal to represent the basis on which the choices are made (the states),*
  - *and one signal to define the agent's goal (the rewards).*

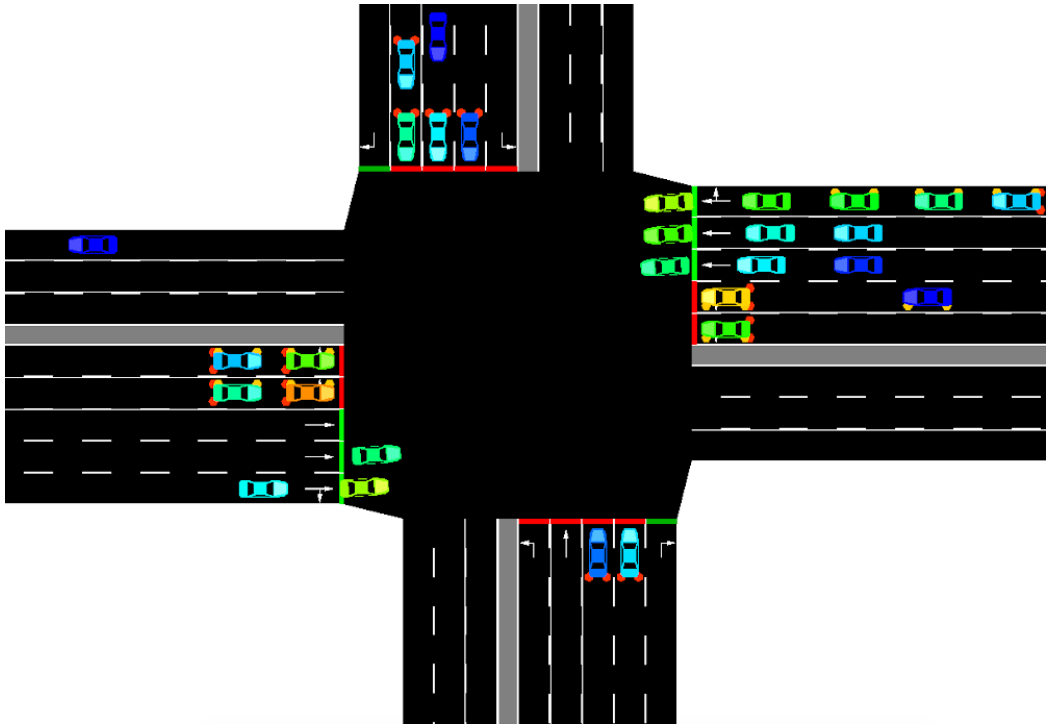
MDP Formalization : Video Games

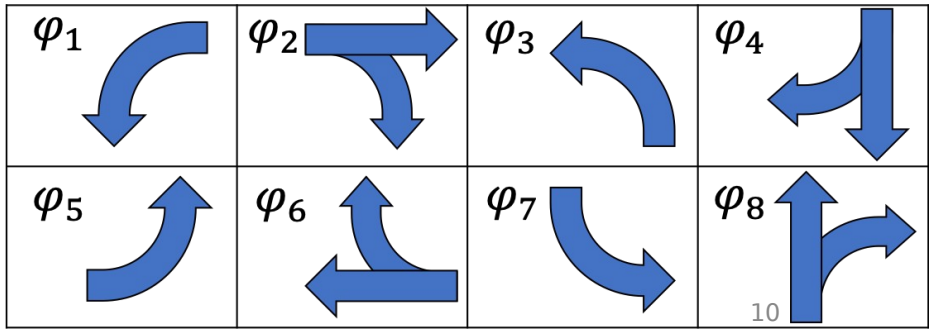
- *State:*
  - *raw pixels*
- *Actions:*
  - *game controls*
- *Reward:*
  - *change in score*
- *State-transition probabilities:*
  - *defined by stochasticity in game evolution*

Ref: Playing Atari with deep reinforcement learning", Mnih et al., 2013

MDP Formalization : Traffic Signal Control

- *State:*
  - *Current signal assignment (green, yellow, and red assignment for each phase)*
  - *For each lane: number of approaching vehicles, accumulated waiting time, number of stopped vehicles, and average speed of approaching vehicles*
- *Actions:*
  - *signal assignment*
- *Reward:*
  - *Reduction in traffic delay*
- *State-transition probabilities:*
  - *defined by stochasticity in approaching demand*





Ref: "Learning an Interpretable Traffic Signal Control Policy", Ault et al., 2020

MDP Formalization : Recycling Robot (Detailed Ex.)

- *Robot has*
  - *sensors for detecting cans*
  - *arm and gripper that can pick the cans and place in an onboard bin;*
- *Runs on a rechargeable battery*
- *Its control system has components for interpreting sensory information, for navigating, and for controlling the arm and gripper*
- *Task for the RL Agent: Make high-level decisions about how to search for cans based on the current charge level of the battery*

MDP Formalization : Recycling Robot (Detailed Ex.)

- *State:*
  - *Assume that only two charge levels can be distinguished*
  - *S = {high, low}*
- *Actions:*
  - *A(high) = {search, wait}*
  - *A(low) = {search, wait, recharge}*
- *Reward:*
  - *Zero most of the time, except when securing a can*
  - *Cans are secured by searching and waiting, but* $r_{search} > r_{wait}$
- *State-transition probabilities:*
  - *[Next Slide]*

MDP Formalization : Recycling Robot (Detailed Ex.)

- *State-transition probabilities (contd...):*

s	a	s'	$p(s'\|s,a)$	$r(s,a,s')$
high	search	high	α	r_{search}
high	search	low	$1-\alpha$	r_{search}
low	search	high	$1-\beta$	-3
low	search	low	β	r_{search}
high	wait	high	1	r_{wait}
high	wait	low	0	-
low	wait	high	0	-
low	wait	low	1	r_{wait}
low	recharge	high	1	0
low	recharge	low	0	-

MDP Formalization : Recycling Robot (Detailed Ex.)

- *State-transition probabilities (contd...):*

s	a	s'	$p(s' \mid s, a)$	$r(s, a, s')$
high	search	high	α	r_{search}
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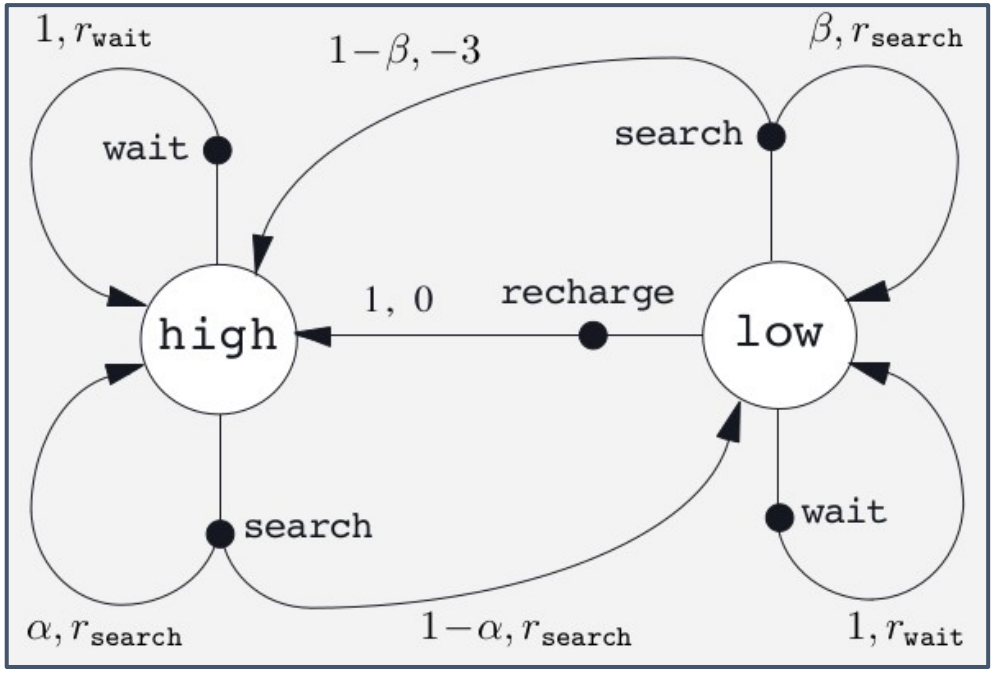
low	search	low	β	r_{search}
high	wait	high	1	r_{wait}
high	wait	low	0	-
low	wait	high	0	-
low	wait	low	1	r_{wait}
low	recharge	high	1	0
low	recharge	low	0	-



Class #3 ends

Note on Goals & Rewards

- *Reward Hypothesis:*

  All of what we mean by goals and purposes can be well thought of as the maximization of the expected value of the cumulative sum of a received scalar signal (called reward).

- *The rewards we set up truly indicate what we want accomplished,*
  - *not the place to impart prior knowledge on how we want it to do*
- *Ex: Chess Playing Agent*
  - *If the agent is rewarded for taking opponents pieces, the agent might fall for the opponent's trap.*
- *Ex: Vacuum Cleaner Agent*
  - *If the agent is rewarded for each unit of dirt it sucks, it can repeatedly deposit and suck the dirt for larger reward*

Returns & Episodes

- *Goal is to maximize the expected return*
- *Return (Gt) is defined as some specific function of the reward sequence*
- *Episodic tasks vs. Continuing tasks*
- *When there is a notion of final time step, say T, return can be*

$$G_t \doteq R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$$

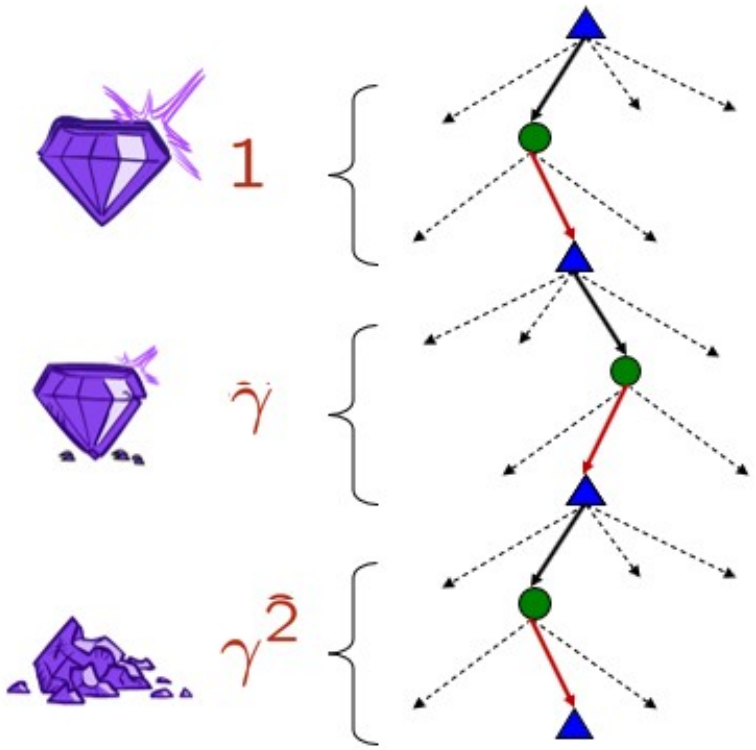
  - *Applicable when agent-environment interaction breaks into episodes*
  - *Ex: Playing Game, Trips through maze etc. [called episodic tasks]*

Returns & Episodes

- *Generally $T = \infty$*
  - *What if the agent receive a reward of +1 for each timestep?*
  - *Discounted Return:*

$$G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

Note: γ is a parameter, $0 \leq \gamma \leq 1$, called the *discount rate*.



  - *Discount rate determines the present value of future rewards*

Returns & Episodes

- *What if γ is 0?*
- *What if γ is 1?*
- *Computing discounted rewards incrementally*

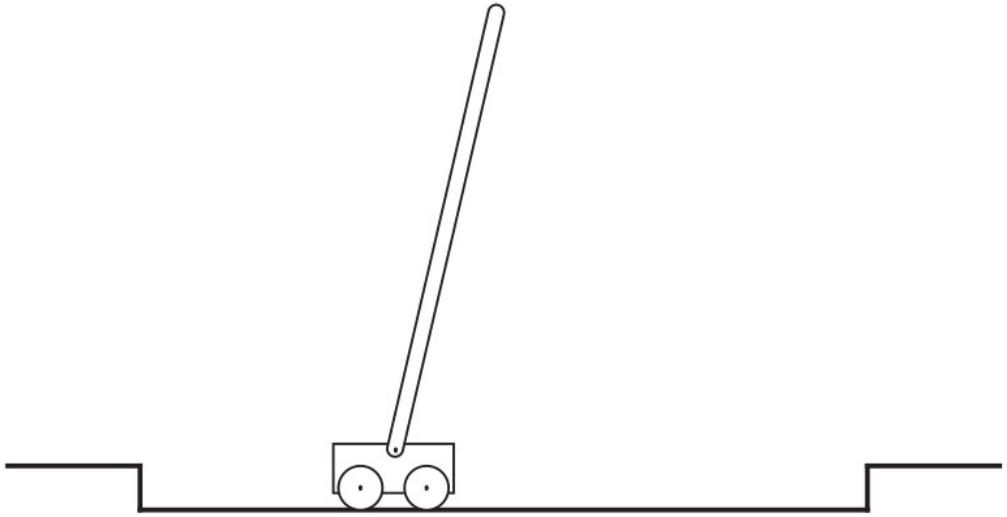
$$
\begin{aligned}
G_t &\doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 R_{t+4} + \cdots \\
&= R_{t+1} + \gamma \left(R_{t+2} + \gamma R_{t+3} + \gamma^2 R_{t+4} + \cdots \right) \\
&= R_{t+1} + \gamma G_{t+1}
\end{aligned}
$$

- *Sum of an infinite number of terms, it is still finite if the reward is nonzero and constant and if γ < 1.*
- *Ex: reward is +1 constant*

$$G_t = \sum_{k=0}^{\infty} \gamma^k = \frac{1}{1-\gamma}.$$

Returns & Episodes

- *Objective: To apply forces to a cart moving along a track so as to keep a pole hinged to the cart from falling over*
- *Discuss:*
  - *Consider the task as episodic, that is try/maintain balance until failure. What could be the reward function?*
  - *Repeat prev. assuming task is continuous.*



Policy

- A mapping from states to probabilities of selecting each possible action.
  - $\pi(a|s)$ is the probability that $A_t = a$ if $S_t = s$
- The purpose of learning is to improve the agent's policy with its experience

Defining Value Functions

State-value function for policy π

$$v_\pi(s) \doteq \mathbb{E}_\pi[G_t \mid S_t = s] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s\right], \text{ for all } s \in \mathcal{S},$$

Action-value function for

$$q_\pi(s,a) \doteq \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s, A_t = a\right]$$

Defining Value Functions

State Value function in terms of Action-value function for policy π

$$v_\pi(s) = \sum_{a \in \mathcal{A}(s)} \pi(a|s) q_\pi(s,a)$$

Action Value function in terms of State value function for policy π

$$q_\pi(s,a) = \sum_{s \in \mathcal{S}} \sum_{r \in \mathcal{R}} p(s', r \,|\, s, a) \left[r + \gamma v_\pi(s') \right]$$

$$q_\pi(s,a) = \sum_{s\in\mathcal{S}} \sum_{r\in\mathcal{R}} p(s',r|s,a)\left[r + \gamma v_\pi(s')\right]$$

Suppose:

- From s, action a leads to:
  - s_1 with probability 0.7, reward = 5
  - s_2 with probability 0.3, reward = 2
- $v_\pi(s_1) = 10$
- $v_\pi(s_2) = 4$
- $\gamma = 0.9$

Compute:

$$q_\pi(s,a)$$

$$= 0.7[5 + 0.9(10)] + 0.3[2 + 0.9(4)]$$

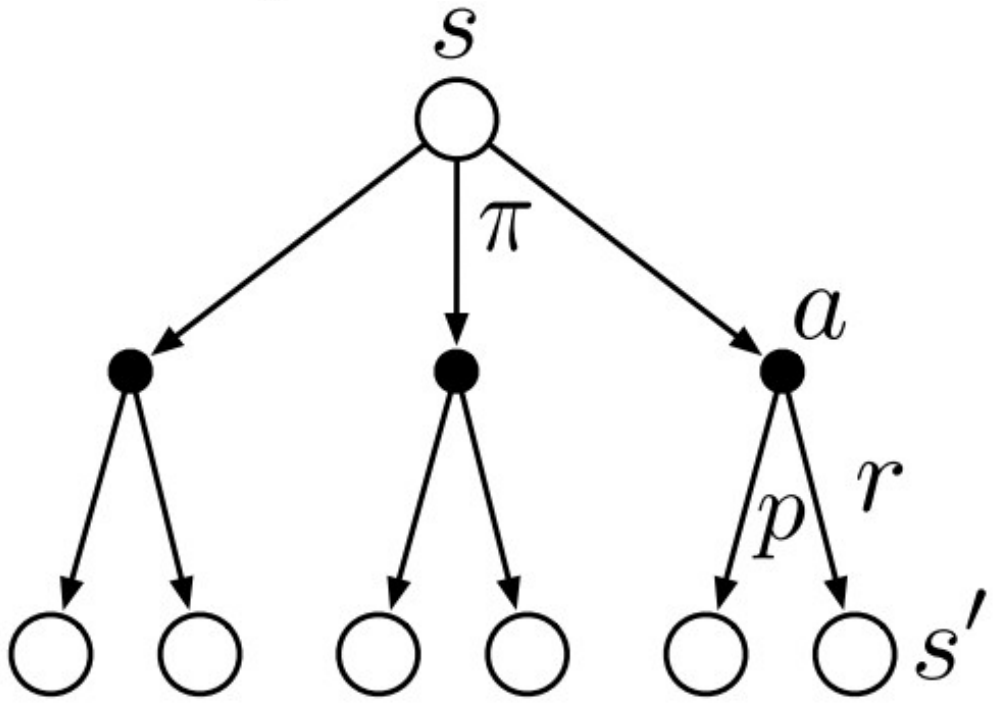
$$= 0.7[14] + 0.3[5.6]$$

$$= 9.8 + 1.68 = 11.48$$

Bellman Equation for V_π

$$v_\pi(s) \doteq \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\left[r + \gamma v_\pi(s')\right]$$

Value of the start state must equal
(1)the (discounted) value of the expected next state,
plus
(2)the reward expected along the way

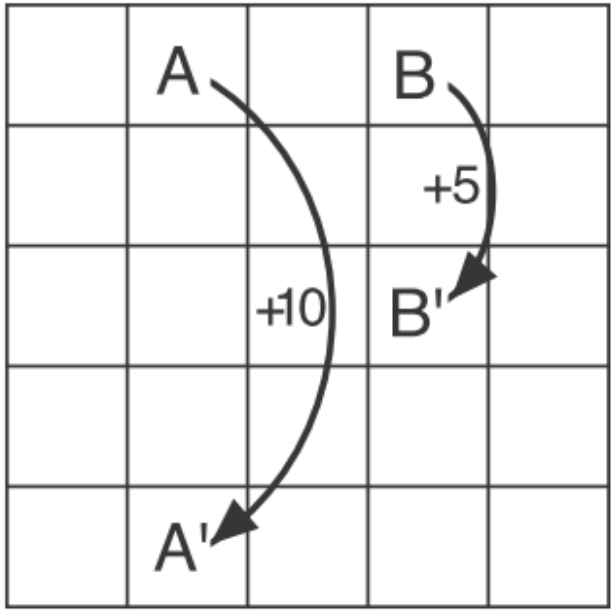


Backup Diagram

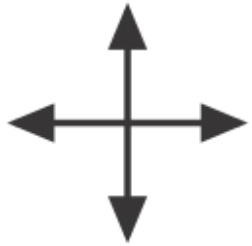
Understanding $V_{\pi}(s)$ with Gridworld

Reward:

- -1 if an action takes agent off the grid
- Exceptional reward from A and B for all actions taking agent to A' and B' resp.
- 0 everywhere else



Exceptional reward dynamics



Actions

3.3	8.8	4.4	5.3	1.5
1.5	3.0	2.3	1.9	0.5
0.1	0.7	0.7	0.4	-0.4
-1.0	-0.4	-0.4	-0.6	-1.2
-1.9	-1.3	-1.2	-1.4	-2.0

State-value function for the equiprobable random policy with γ = 0.9

Understanding $V_{\pi}(s)$ with Gridworld

$$v_\pi(s) \doteq \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\left[r + \gamma v_\pi(s')\right]$$

Verify $V_{\pi}(s)$ using Bellman equation for this state with $\gamma = 0.9$, and equiprobable random policy

3.3	8.8	4.4	5.3	1.5
1.5	3.0	2.3	1.9	0.5
0.1	0.7	0.7	0.4	-0.4
-1.0	-0.4	-0.4	-0.6	-1.2
-1.9	-1.3	-1.2	-1.4	-2.0

Understanding $V_{\pi}(s)$ with Gridworld

$$v_\pi(s) \doteq \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\left[r + \gamma v_\pi(s')\right]$$

$$\begin{aligned} v_\pi(s) &= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\left[r + \gamma v_\pi(s')\right] \\ &= \sum_a 0.25 \cdot \left[0 + 0.9 \cdot (2.3 + 0.4 - 0.4 + 0.7)\right] \\ &= 0.25 \cdot [0.9 \cdot 3.0] = 0.675 \approx 0.7 \end{aligned}$$

3.3	8.8	4.4	5.3	1.5
1.5	3.0	2.3	1.9	0.5
0.1	0.7	0.7	0.4	-0.4
-1.0	-0.4	-0.4	-0.6	-1.2
-1.9	-1.3	-1.2	-1.4	-2.0

Ex-1

Recollect the reward function used for Gridworld as below:

- -1 if an action takes agent off the grid
- Exceptional reward from A and B for all actions taking agent to A’ and B’ resp.
- 0, everywhere else

Let us add a constant c (say 10) to the rewards of all the actions. Will it change anything?

Optimal Policies and Optimal Value Functions

- $\pi \geq \pi'$ if and only if $v_\pi(s) \geq v_\pi(s)$ for all $s \in S$
- There is always at least one policy that is better than or equal to all other policies → optimal policy (denoted as π_*)
  - There could be more than one optimal policy !!!

Optimal state-value function

$$v_*(s) \doteq \max_\pi v_\pi(s)$$

Optimal action-value function

$$q_*(s,a) \doteq \max_\pi q_\pi(s,a)$$

$$q_*(s,a) = \mathbb{E}[R_{t+1} + \gamma v_*(S_{t+1}) \mid S_t = s, A_t = a]$$

$$q_*(s,a) = \mathbb{E}\left[R_{t+1} + \gamma v_*(S_{t+1}) \mid S_t = s, A_t = a\right]$$

Small MDP

States: $S = \{A, B, T\}$ where T is terminal.

Discount: $\gamma = 0.9$

Actions and rewards (deterministic)

From A:

- Left: goes to B, reward $+2$
- Right: goes to T, reward $+5$

From B:

- Up: goes to T, reward $+4$
- Down: goes to T, reward $+4$ ✅ (same reward, different action)

Terminal T: value 0

Step 1: Compute $v_*(B)$

At B, both actions give same return:

$$q_*(B, \text{Up}) = 4 + 0.9 \cdot 0 = 4$$

$$q_*(B, \text{Down}) = 4 + 0.9 \cdot 0 = 4$$

So,

$$v_*(B) = \max(4, 4) = 4$$

✅ And there are two optimal actions at B (Up or Down), so multiple optimal policies exist.

Step 2: Compute $q_*(A, \cdot)$

For action Right (A → T):

$$q_*(A, \text{Right}) = 5 + 0.9 \cdot 0 = 5$$

For action Left (A → B):

$$q_*(A, \text{Left}) = 2 + 0.9 \cdot v_*(B) = 2 + 0.9 \cdot 4 = 2 + 3.6 = 5.6$$

So:

$$q_*(A, \text{Left}) = 5.6, \quad q_*(A, \text{Right}) = 5$$

Step 3: Compute $v_*(A)$

$$v_*(A) = \max(5.6,\ 5) = 5.6$$

So the optimal action at A is Left.

Final Answers (summary)

- $v_*(B) = 4$
- $q_*(B, \text{Up}) = 4,\ q_*(B, \text{Down}) = 4$
- $q_*(A, \text{Left}) = 5.6,\ q_*(A, \text{Right}) = 5$
- $v_*(A) = 5.6$

Optimal policy π^*

- At A: choose Left
- At B: choose Up OR Down

✅ Hence more than one optimal policy:

- π_1^* : $A \rightarrow$ Left, $B \rightarrow$ Up
- π_2^* : $A \rightarrow$ Left, $B \rightarrow$ Down

Optimal Policies and Optimal Value Functions

Bellman optimality equation - expresses that *the value of a state under an optimal policy must equal the expected return for the best action from that state*

$$
\begin{aligned}
v_*(s) &= \max_{a \in \mathcal{A}(s)} q_{\pi_*}(s,a) \\
&= \max_a \mathbb{E}_{\pi_*}[G_t \mid S_t = s, A_t = a] \\
&= \max_a \mathbb{E}_{\pi_*}[R_{t+1} + \gamma G_{t+1} \mid S_t = s, A_t = a] \\
&= \max_a \mathbb{E}[R_{t+1} + \gamma v_*(S_{t+1}) \mid S_t = s, A_t = a] \\
&= \max_a \sum_{s',r} p(s', r \mid s, a)\big[r + \gamma v_*(s')\big].
\end{aligned}
$$

Bellman optimality equation for V_*

Optimal Policies and Optimal Value Functions

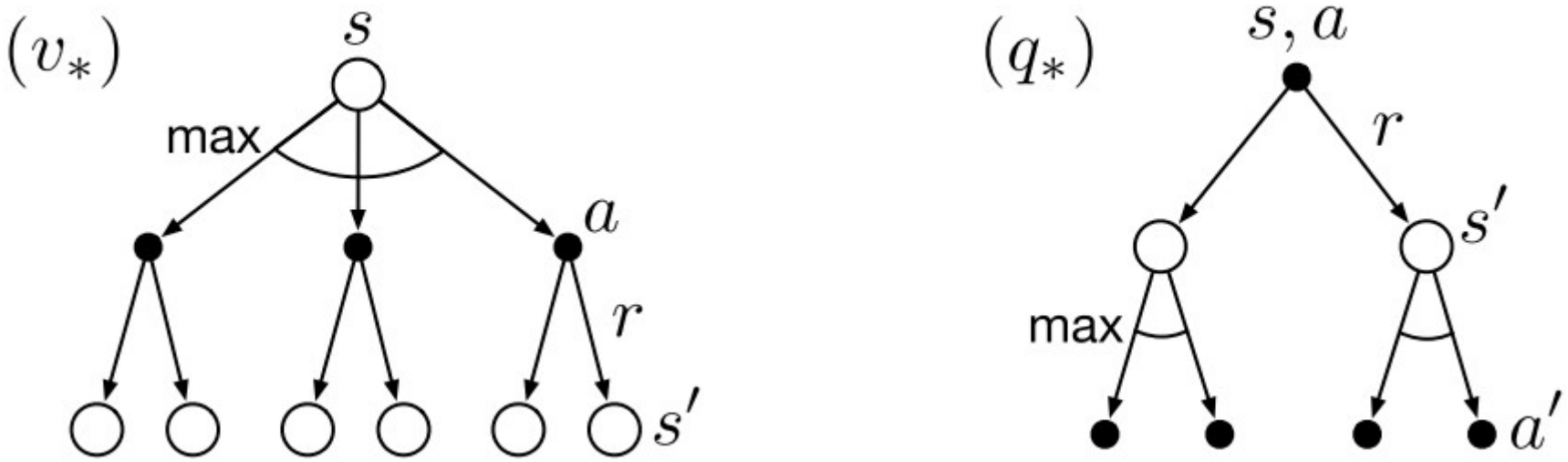
Bellman optimality equation - expresses that *the value of a state under an optimal policy must equal the expected return for the best action from that state*

Bellman optimality equation for q_*

$$
\begin{aligned}
q_*(s,a) &= \mathbb{E}\left[R_{t+1} + \gamma \max_{a'} q_*(S_{t+1}, a') \;\middle|\; S_t = s, A_t = a\right] \\
&= \sum_{s',r} p(s', r \mid s, a)\left[r + \gamma \max_{a'} q_*(s', a')\right].
\end{aligned}
$$

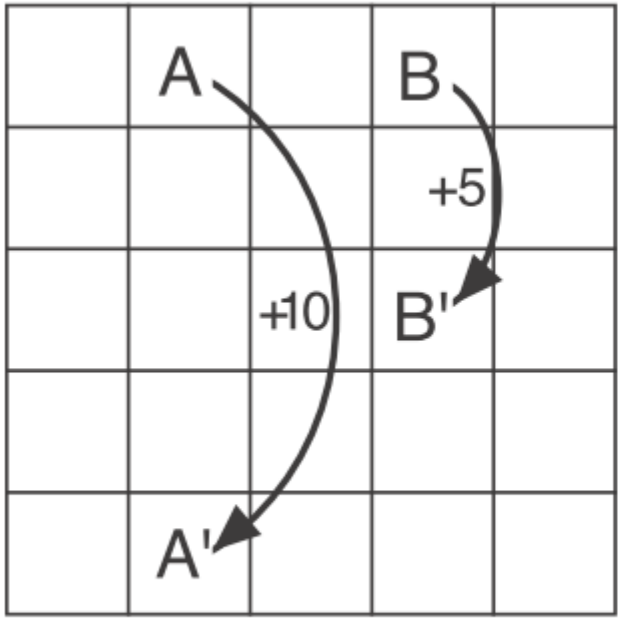
Optimal Policies and Optimal Value Functions

Bellman optimality equation - expresses that *the value of a state under an optimal policy must equal the expected return for the best action from that state*



Backup diagrams for v* and q*

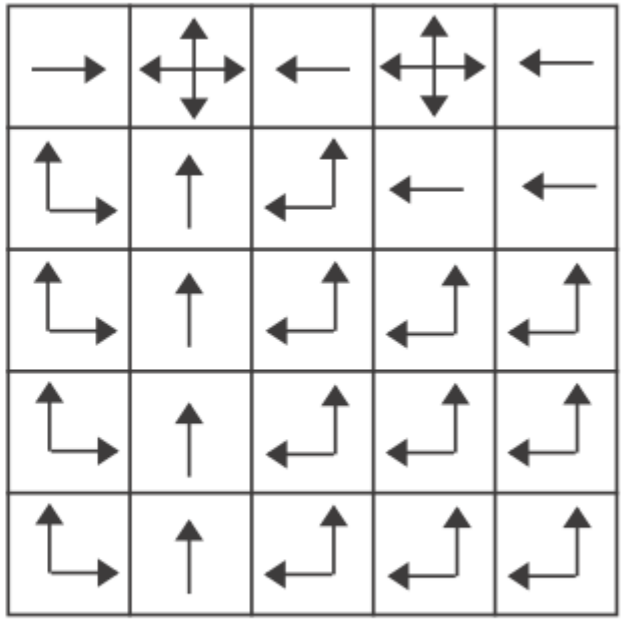
Optimal solutions to the gridworld example



Gridworld

22.0	24.4	22.0	19.4	17.5
19.8	22.0	19.8	17.8	16.0
17.8	19.8	17.8	16.0	14.4
16.0	17.8	16.0	14.4	13.0
14.4	16.0	14.4	13.0	11.7

v_*



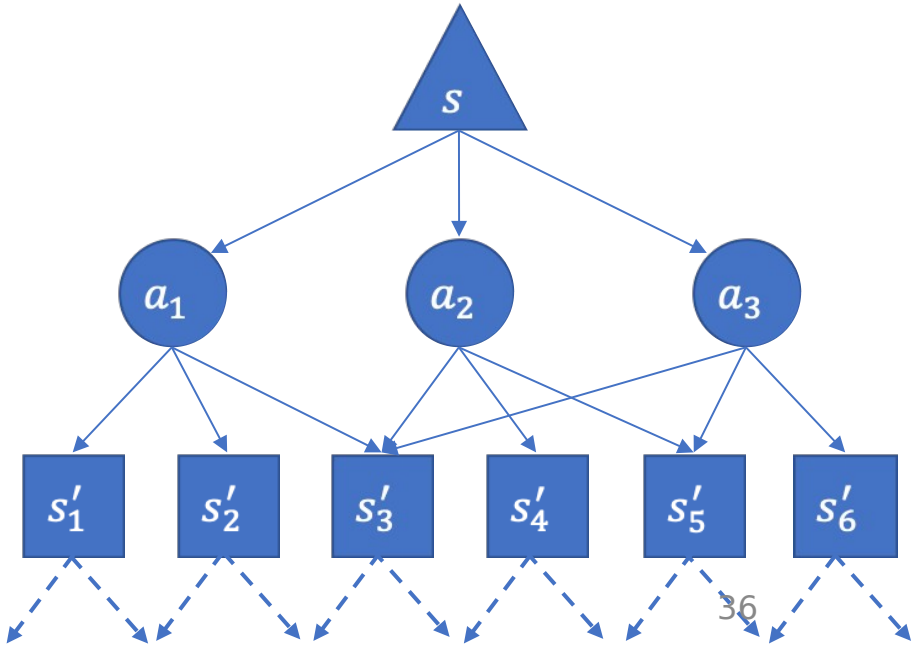
π_*

Backup diagrams for v* and q*

MDP - Objective

A set of states $s \in \mathcal{S}$
A set of actions $a \in \mathcal{A}$
State-transition probabilities $P(s'|s,a)$
A reward function $R(s,a,s')$

- Compute a policy: what action to take at each state
  - $\pi: S \rightarrow A$
- Compute the **optimal** policy: maximum expected reward, π^*
- $\pi^*(s) = ?$
- $= \underset{a}{\text{argmax}}[\sum_{s'} P(s'|s,a)R(s,a,s')]$
  - Must also optimize over the future (next steps)
- $= \underset{a}{\text{argmax}}[\sum_{s'} P(s'|s,a)\,(R(s,a,s') + \underbrace{\mathbb{E}_{\pi^*}[G|s']}_{v^*(s')})]$



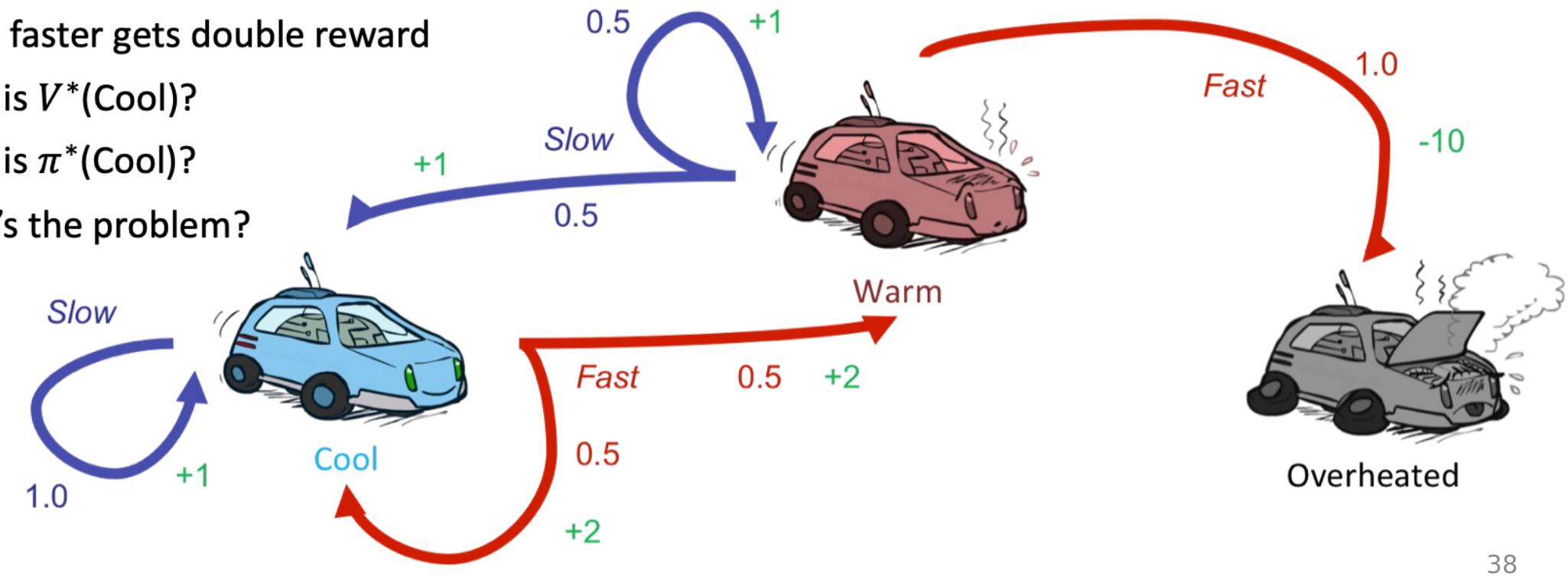
Notation

- π^* - a policy that yields the maximal expected sum of rewards
- G- observed sum of rewards, i.e., $\sum r_t$
- $v^*(s)$ - the expected sum of rewards from being at s then following π^*
  - $= \mathbb{E}_{\pi^*}[G|s]$

Race car example

$$\max_a \left[\sum_{s'} P(s'|s,a) \left(R(s,a,s') + v^*(s') \right) \right]$$

- A robot car wants to travel far, quickly
- Three states: Cool, Warm, Overheated
- Two actions: *Slow*, *Fast*
- Going faster gets double reward
- What is V^*(Cool)?
- What is π^*(Cool)?
- What's the problem?



🚗 Problem Setup

States:

- Cool
- Warm
- Overheated (terminal/bad state)

Actions:

- Slow
- Fast

Rewards:

- Slow → +1
- Fast → +2
- Overheated → -10

Discount factor:

$$\gamma - 1$$

🔵 Transition Dynamics

From Cool

- Slow:
  - 1.0 → Cool, reward +1
- Fast:
  - 0.5 → Cool, reward +2
  - 0.5 → Warm, reward +2

From Warm

- Slow:
  - 0.5 → Cool, reward +1
  - 0.5 → Warm, reward +1
- Fast:
  - 1.0 → Overheated, reward -10

🎯 Goal

Find:

1. $V^*(Cool)$
2. $\pi^*(Cool)$
3. What is the problem?

🧠 Step 1: Value of Overheated

Terminal bad state:

$$V^*(Overheated) = 0$$

(Reward -10 is received upon entering it.)

🟣 Step 2: Solve for Warm

Compute Q-values.

If Warm → Fast

$$Q(Warm, Fast) = -10 + 0 = -10$$

Bad idea.

$$\max_a \left[\sum_{s'} P(s'|s,a) \left(R(s,a,s') + \gamma V^*(s') \right) \right]$$

If Warm → Slow

$$Q(Warm, Slow) = 0.5(1 + V(Cool)) + 0.5(1 + V(Warm))$$

So:

$$= 1 + 0.5V(Cool) + 0.5V(Warm)$$

Since Fast is terrible:

$$V(Warm) = Q(Warm, Slow)$$

So:

$$V(Warm) = 1 + 0.5V(Cool) + 0.5V(Warm)$$

Rearrange:

$$0.5V(Warm) = 1 + 0.5V(Cool)$$

$$V(Warm) = 2 + V(Cool)$$

Step 3: Solve for Cool

Now compute Q-values.

Cool → Slow

$$Q(Cool, Slow) = 1 + V(Cool)$$

Cool → Fast

$$Q(Cool, Fast) = 0.5(2 + V(Cool)) + 0.5(2 + V(Warm))$$

Substitute $V(Warm) = 2 + V(Cool)$:

$$= 0.5(2 + V(Cool)) + 0.5(2 + 2 + V(Cool))$$

$$= 0.5(2 + V(Cool)) + 0.5(4 + V(Cool))$$

$$= 1 + 0.5V(Cool) + 2 + 0.5V(Cool)$$

$$= 3 + V(Cool)$$

🎯 Compare Actions at Cool

- Slow → $1 + V(Cool)$
- Fast → $3 + V(Cool)$

Clearly:

$$Fast > Slow$$

So:

$$\pi^*(Cool) = Fast$$

🚨 What's the Problem?

This looks weird because:

$$V(Cool) = 3 + V(Cool)$$

This suggests:

$$V(Cool) = \infty$$

🧨 The Real Issue

Because:

- $\gamma = 1$
- No penalty for staying Cool
- Infinite looping gives infinite reward

So optimal strategy is:

> Keep driving fast forever and collect infinite reward.

This is not realistic.

Grid World:

a(10) — b — c — d — e(1)

Rewards are obtained only after taking Exit.

Quiz 1: $\gamma = 1$

No discounting → future rewards do not lose value.

Since $10 > 1$, always move toward a.

$$\boxed{a: \ Exit, \quad b: W, \quad c: W, \quad d: W, \quad e: Exit}$$

Quiz 2: $\gamma = 0.1$

State	Value toward West (10)	Value toward East (1)	Best
b	$10\gamma = 1$	$\gamma^3 = 0.001$	West
c	$10\gamma^2 = 0.1$	$\gamma^2 = 0.01$	West
d	$10\gamma^3 = 0.01$	$\gamma = 0.1$	East

$$\boxed{a: \ Exit, \quad b: W, \quad c: W, \quad d: E, \quad e: Exit}$$

Quiz 3: For which γ are West and East equally good in state d?

From state d, compare the discounted return for going West versus East.

Going East:

$d \to e \to Exit$

The reward 1 is received when exiting from e. Therefore,

$$Q(d, \text{East}) = \gamma(1) = \gamma$$

Going West:

$d \to c \to b \to a \to Exit$

The reward 10 is received only after reaching a and taking Exit. It is three steps farther away from d, so

$$Q(d, \text{West}) = 10\gamma^3$$

For East and West to be equally good:

$$10\gamma^3 = \gamma$$

Assuming $\gamma > 0$,

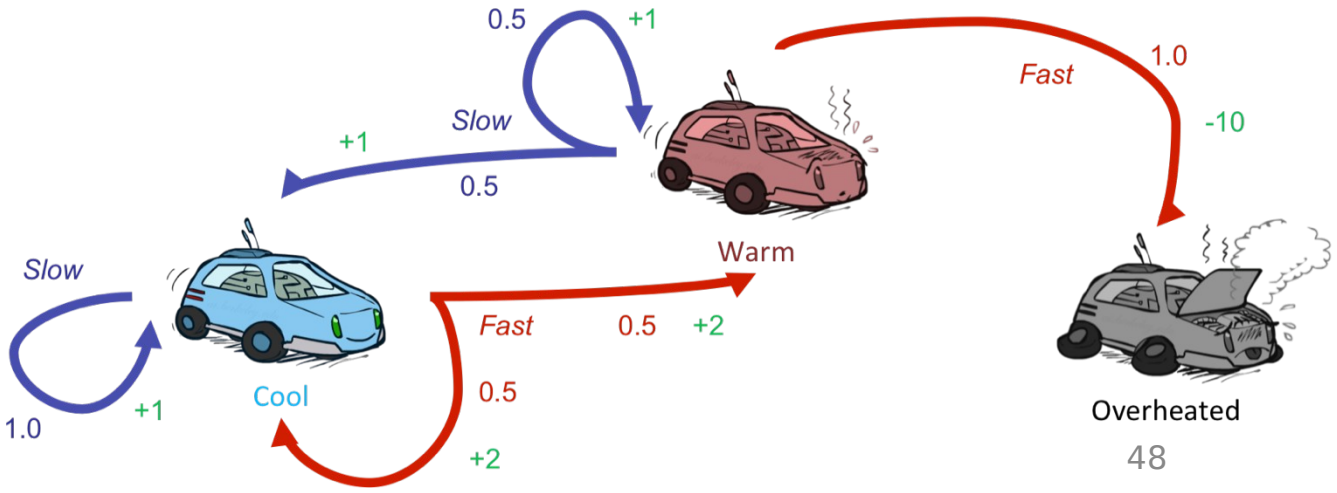
$$10\gamma^2 = 1$$

$$\gamma^2 = 0.1$$

$$\boxed{\gamma = \sqrt{0.1} \approx 0.316}$$

Race car example

- Consider a discount factor, $\gamma = 0.9$
- What is $v^*(Cool)$
- $= \max_a \left[r(s,a) + \sum_{s'} p(s'|s,a)\ \gamma\ v^*(s') \right]$
- $= \max[1 + 0.9 \cdot 1 v^*(Cool), 2 + 0.9 \cdot 0.5 v^*(Cool) + 0.9 \cdot 0.5 v^*(Warm)]$
  - Computing…
  - …Stack overflow
- Work in iterations



Value iteration

Value iteration

Initialize array V arbitrarily (e.g., $V(s) = 0$ for all $s \in \mathcal{S}^+$)

Repeat
$\Delta \leftarrow 0$
For each $s \in \mathcal{S}$:
$v \leftarrow V(s)$
$V(s) \leftarrow \max_a \sum_{s',r} p(s', r \mid s, a)\left[r + \gamma V(s')\right]$
$\Delta \leftarrow \max(\Delta, |v - V(s)|)$
until $\Delta < \theta$ (a small positive number)

Output a deterministic policy, $\pi \approx \pi_*$, such that
$\pi(s) = \arg\max_a \sum_{s',r} p(s', r \mid s, a)\left[r + \gamma V(s')\right]$

Value Iteration

V_0

0 0

0

V_1

2 1

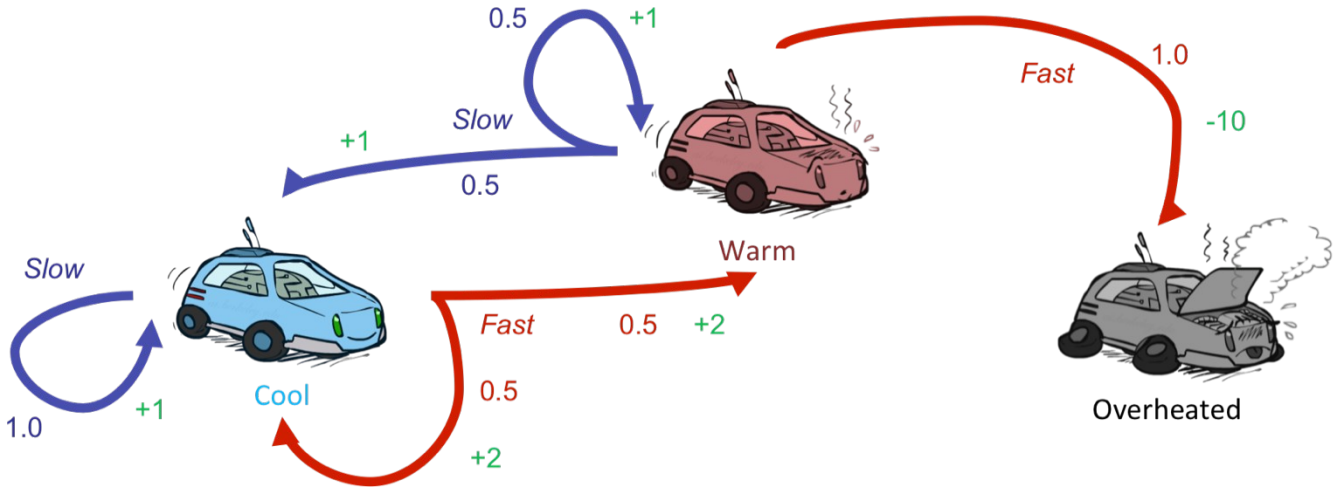
0

V_2

3.35 2.35

0

Check this computation on paper.



$\gamma = 0.9$

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s', r \mid s, a)\left[r + \gamma v_k(s')\right]$$

$$V_0 = [0,\ 0,\ 0]$$

✅ Iteration 1 → V_1

For Cool

- Slow:

$$Q_0(C, \text{Slow}) = 1 + 0.9\,V_0(C) = 1 + 0 = 1$$

- Fast:

$$Q_0(C, \text{Fast}) = 2 + 0.9\big(0.5V_0(C) + 0.5V_0(W)\big) = 2 + 0.9(0) = 2$$

So:

$$V_1(C) = \max(1, 2) = 2$$

For Warm

- Slow:

$$Q_0(W, \text{Slow}) = 1 + 0.9\big(0.5V_0(C) + 0.5V_0(W)\big) = 1$$

- Fast:

$$Q_0(W, \text{Fast}) = -10 + 0.9V_0(O) = -10$$

So:

$$V_1(W) = \max(1, -10) = 1$$

Overheated:

$$V_1(O) = 0$$

✅ Therefore:

$$\boxed{V_1 = [2,\ 1,\ 0]}$$

✅ Iteration 2 → V_2

Now use V_1 values: $V_1(C) = 2,\ V_1(W) = 1$

For Cool

- Slow:

$$Q_1(C, \text{Slow}) = 1 + 0.9V_1(C) = 1 + 0.9(2) = 1 + 1.8 = 2.8$$

- Fast:

$$Q_1(C, \text{Fast}) = 2 + 0.9\big(0.5V_1(C) + 0.5V_1(W)\big)$$

$$= 2 + 0.9\big(0.5(2) + 0.5(1)\big) = 2 + 0.9(1 + 0.5) = 2 + 0.9(1.5) = 2 + 1.35 = 3.35$$

So:

$$V_2(C) = \max(2.8, 3.35) = 3.35$$

For Warm

- Slow:

$$Q_1(W, \text{Slow}) = 1 + 0.9\big(0.5V_1(C) + 0.5V_1(W)\big) = 1 + 0.9(1.5) = 1 + 1.35 = 2.35$$

- Fast:

$$Q_1(W, \text{Fast}) = -10$$

So:

$$V_2(W) = \max(2.35, -10) = 2.35$$

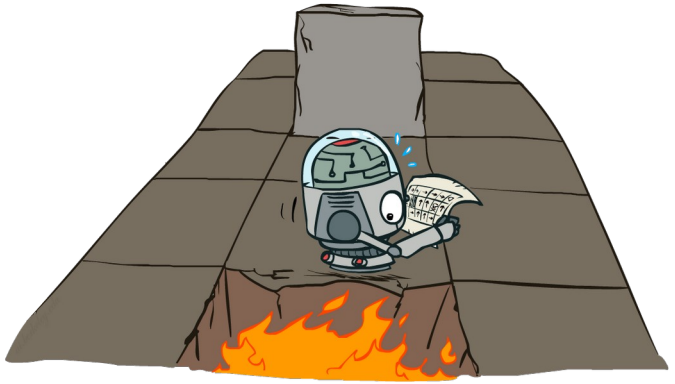
Overheated:

$$V_2(O) = 0$$

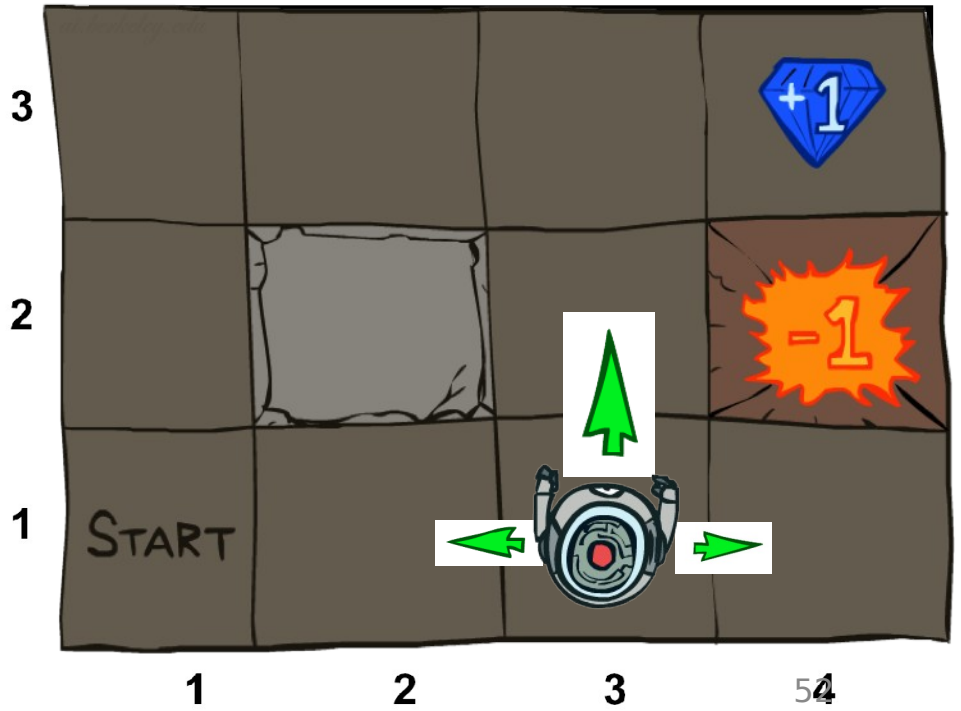
✅ Therefore:

$$\boxed{V_2 = [3.35,\ 2.35,\ 0]}$$

Example: Grid World

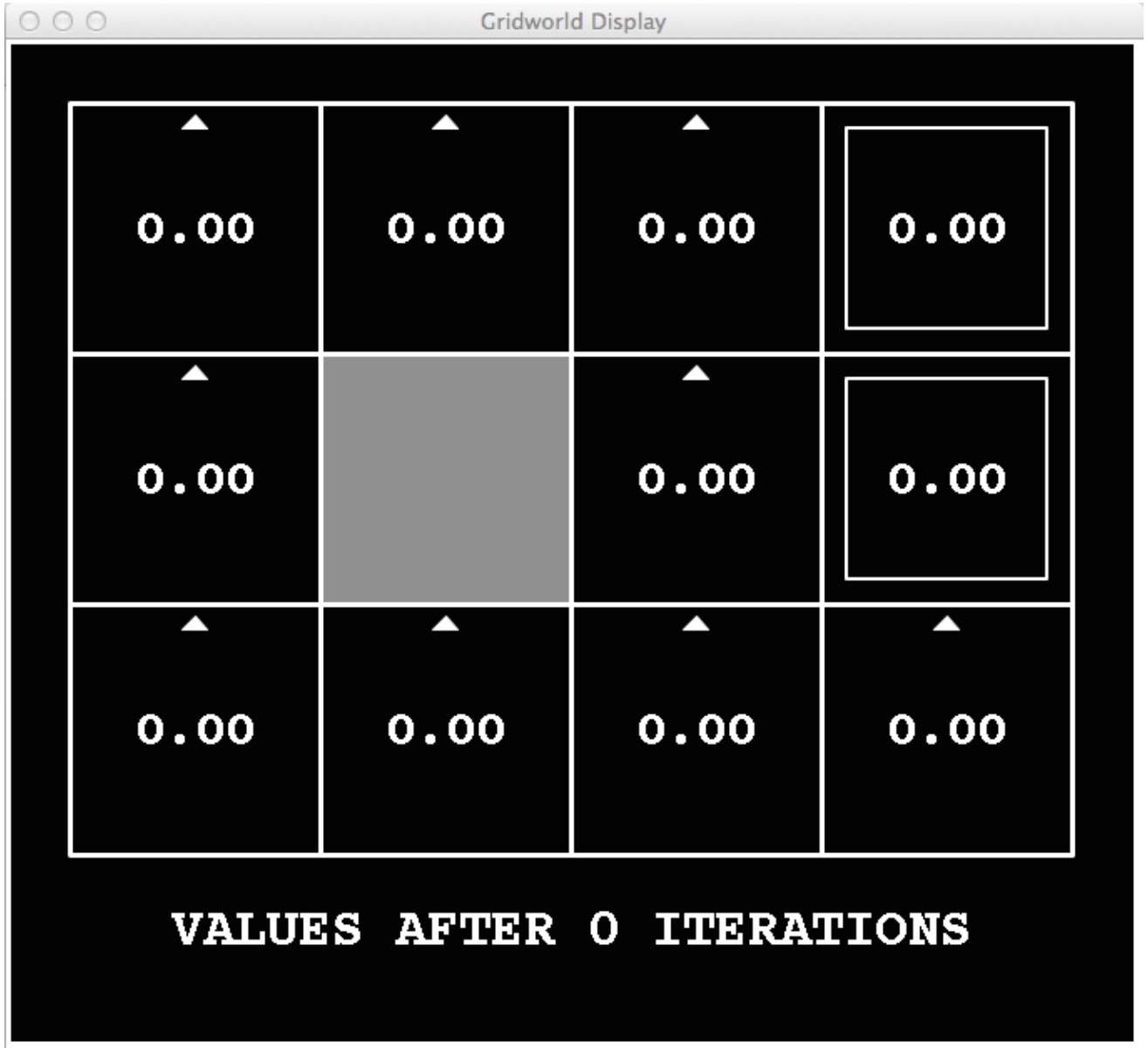


- A maze-like problem
  - The agent lives in a grid
  - Walls block the agent's path
- Noisy movement: actions do not always go as planned
  - 80% of the time, the action North takes the agent North
  - 10% of the time, North takes the agent West; 10% East
  - If there is a wall in the direction the agent would have been taken, the agent stays put
- The agent receives rewards each time step
  - Small negative reward each step (battery drain)
  - Big rewards come at the end (good or bad)
- Goal: maximize sum of (discounted) rewards



k=0

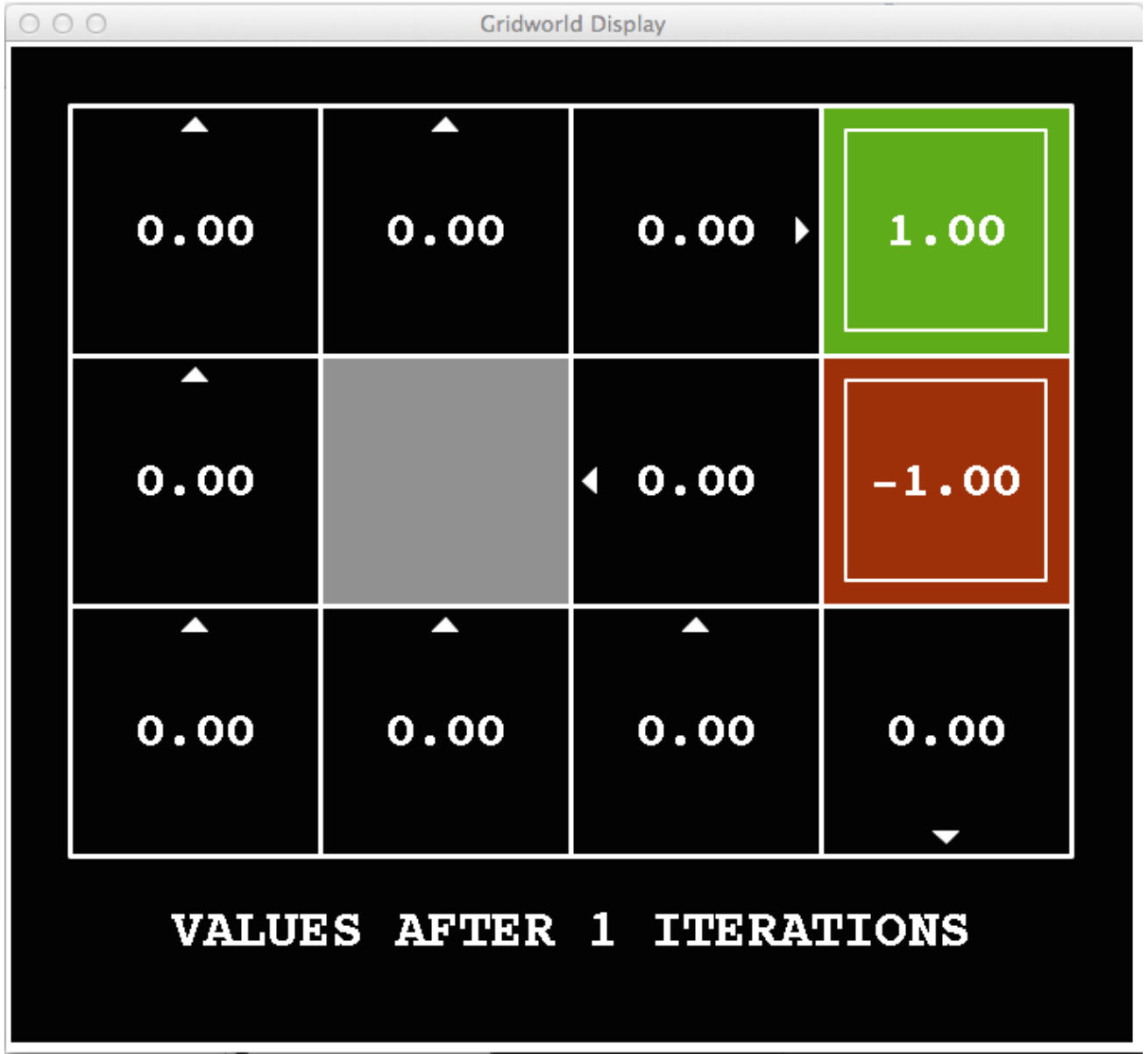
$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$

k=1



Noise = 0.2
Discount = 0.9
Living reward = 0

k=2

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$

Noise = 0.2
Discount = 0.9
Living reward = 0

Why Only the State Left of +1 Becomes 0.72?

Consider the state directly left of +1.

Best action = RIGHT.

Transition probabilities:

Outcome	Prob	Next State
Right	0.8	+1
Slip up	0.1	normal state
Slip down	0.1	normal state

Now compute:

- For +1:

$$r + \gamma V_1(+1) = 0 + 0.9(1) = 0.9$$

- For other states:

$$0 + 0.9(0) = 0$$

So:

$$V_2(s) = 0.8(0.9) + 0.1(0) + 0.1(0)$$

$$= 0.72$$

k=3

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$

Noise = 0.2
Discount = 0.9
Living reward = 0

Value Iteration at $k = 3$ — Calculation of Values

Given: Noise $= 0.2$ → Intended $= 0.8$, Sideways $= 0.1$ each
Discount $\gamma = 0.9$, Living Reward $= 0$

Values from Previous Iteration $k = 2$

0	0	0.72	+1
0	Wall	0	−1
0	0	0	0

Calculate $k = 3$ Values

Best Action	Bellman Calculation	Result
→	$0.8(0.9)(0.72) + 0.1(0.9)(0) + 0.1(0.9)(0)$	0.52
→	$0.8(0.9)(1) + 0.1(0.9)(0.72) + 0.1(0.9)(0)$	0.78
↑	$0.8(0.9)(0.72) + 0.1(0.9)(0) + 0.1(0.9)(-1)$	0.43

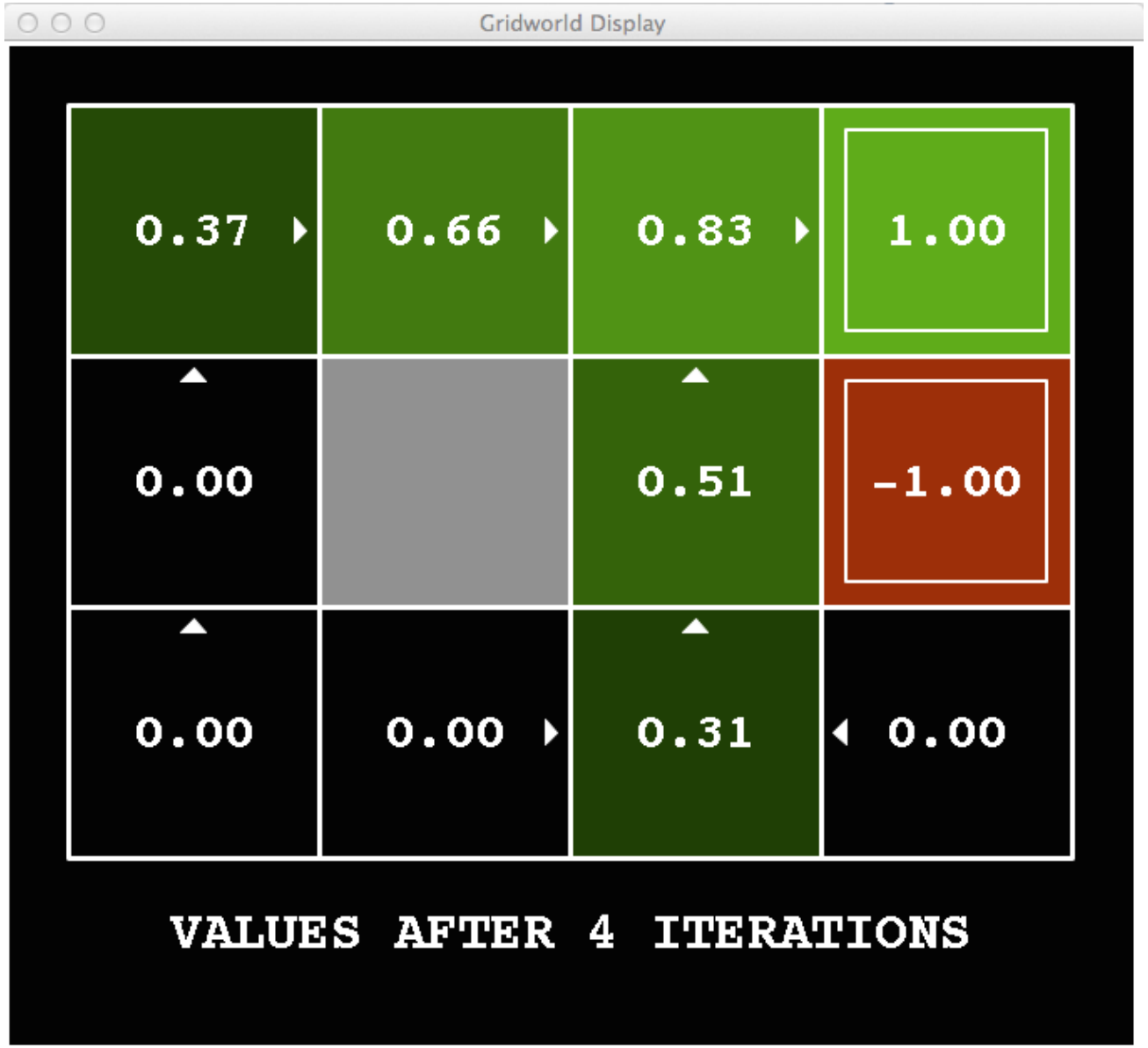
Values After $k = 3$

0	**0.52**	**0.78**	+1
0	Wall	**0.43**	−1
0	0	0	0

Key Point: To calculate V_3, we use only the values from V_2.

k=4

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

Value Iteration at $k = 4$ — How the Values Are Obtained

For $k = 4$, we use the **previous $k = 3$ values**:

0	0.52	0.78	1
0	Wall	0.43	−1
0	0	0	0

Given: $\gamma = 0.9$, intended movement $= 0.8$, sideways movement $= 0.1$ each, living reward $= 0$.

Calculations

Best Action	Calculation using $k = 3$ values	Result
→	$0.8(0.9)(0.52) + 0.1(0.9)(0) + 0.1(0.9)(0)$	**0.37**
→	$0.8(0.9)(0.78) + 0.1(0.9)(0.52) + 0.1(0.9)(0.52)$	**0.66**
→	$0.8(0.9)(1) + 0.1(0.9)(0.78) + 0.1(0.9)(0.43)$	**0.83**
↑	$0.8(0.9)(0.78) + 0.1(0.9)(0.43) + 0.1(0.9)(-1)$	**0.51**
↑	$0.8(0.9)(0.43) + 0.1(0.9)(0) + 0.1(0.9)(0)$	**0.31**

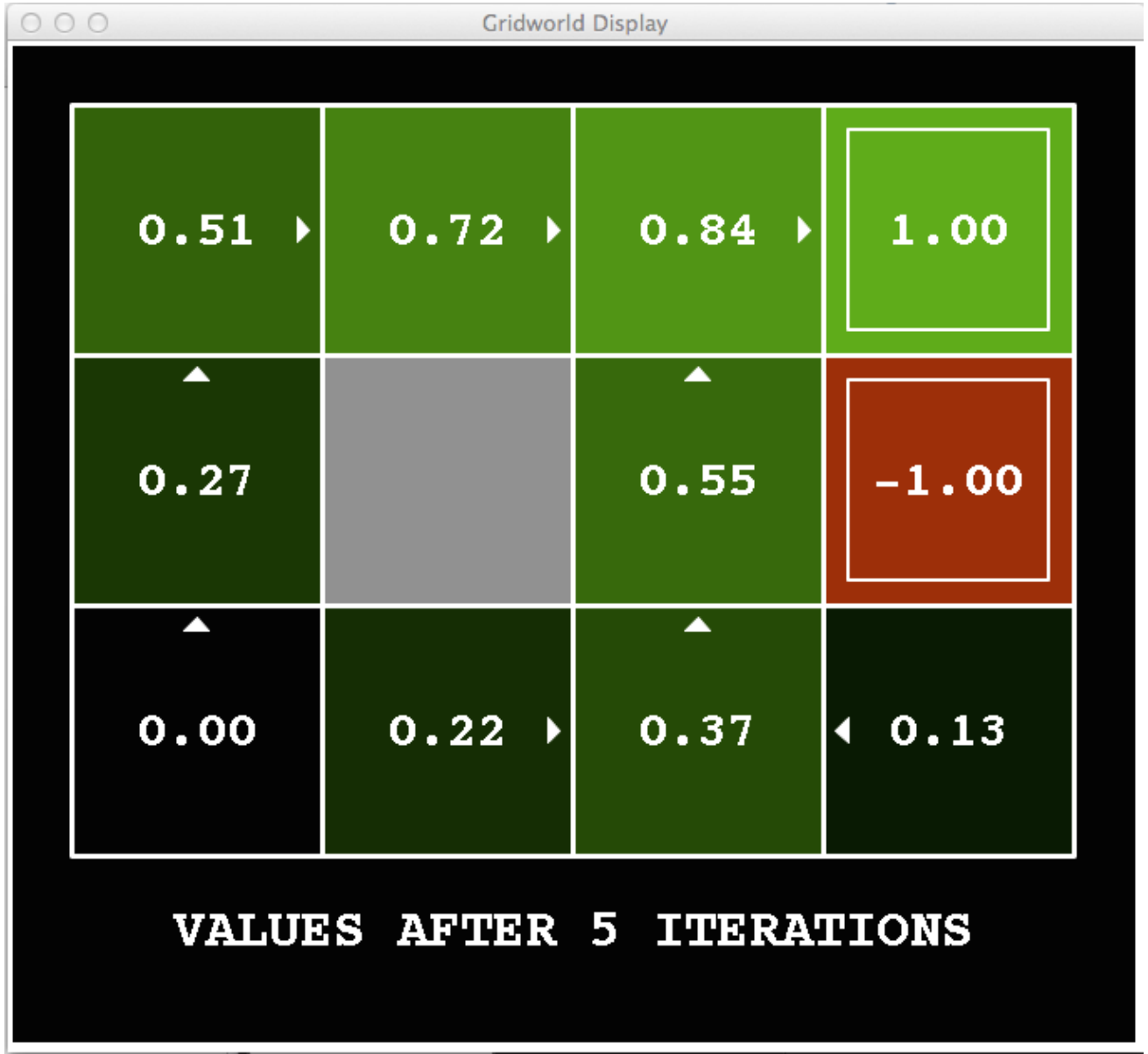
So after $k = 4$:

0.37	0.66	0.83	1
0	Wall	0.51	−1
0	0	0.31	0

Remember: V_4 is calculated entirely from V_3 values.

k=5

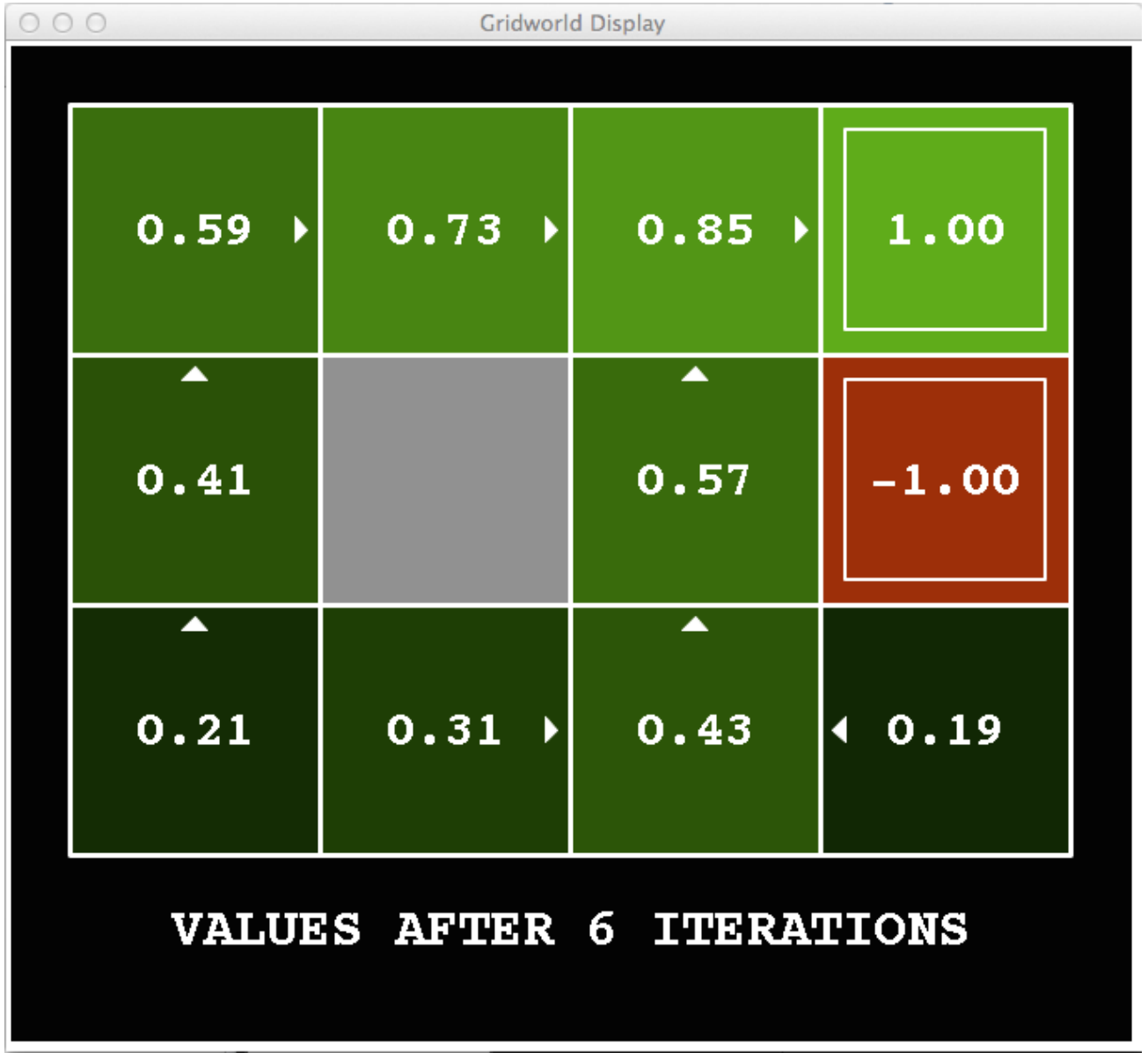
$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

k=6

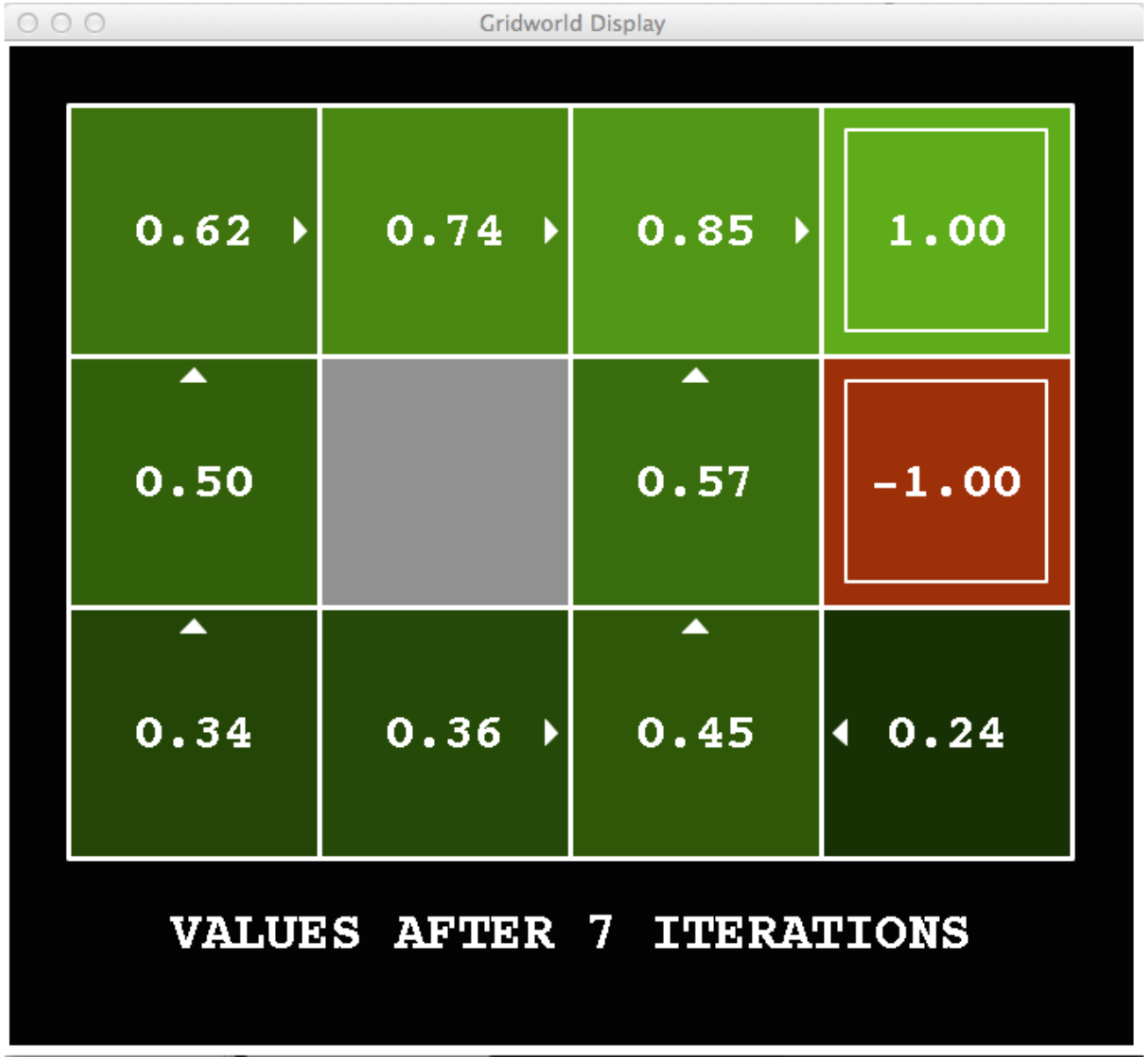
$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$

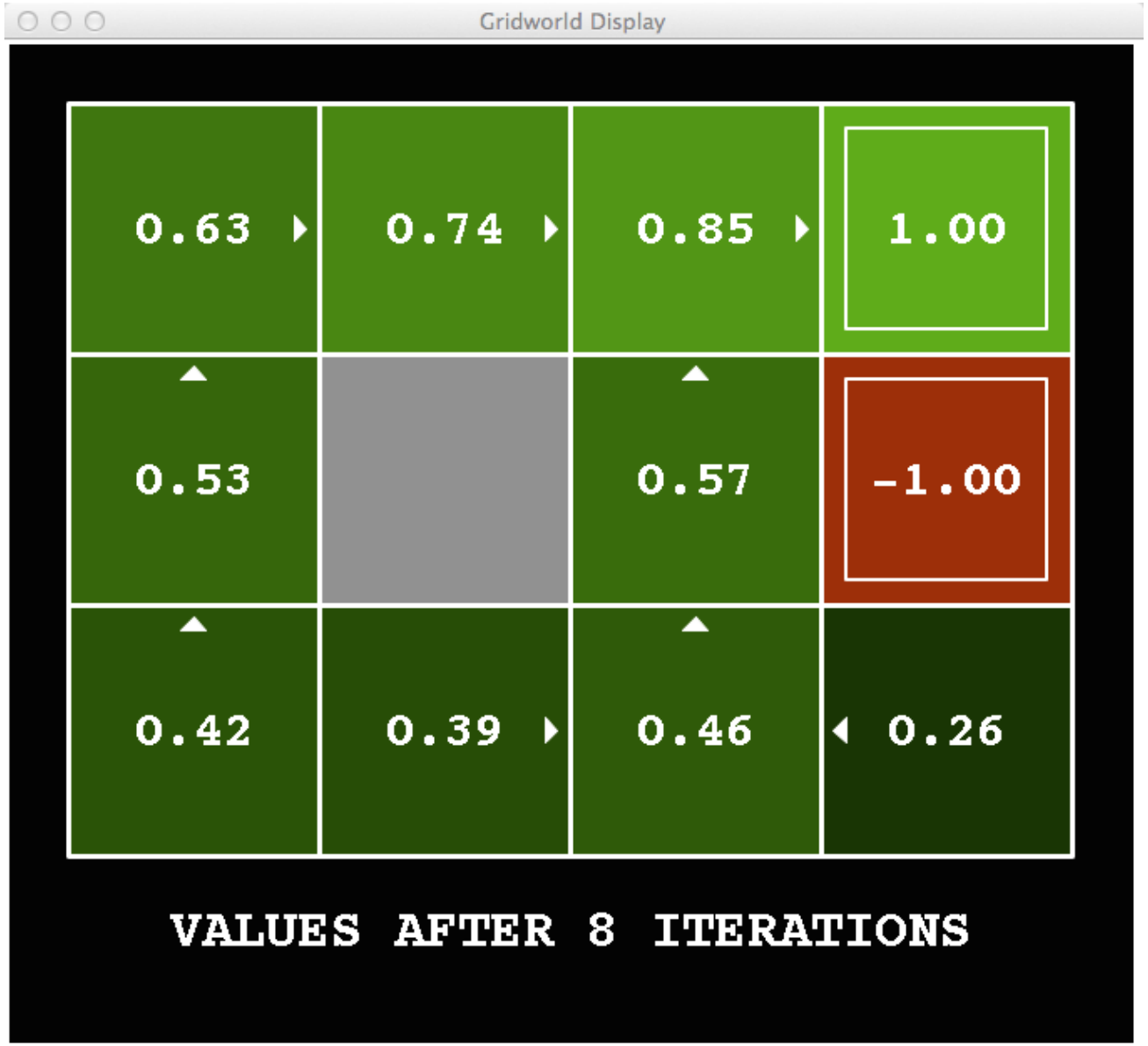
k=7



Noise = 0.2
Discount = 0.9
Living reward = 0

k=8

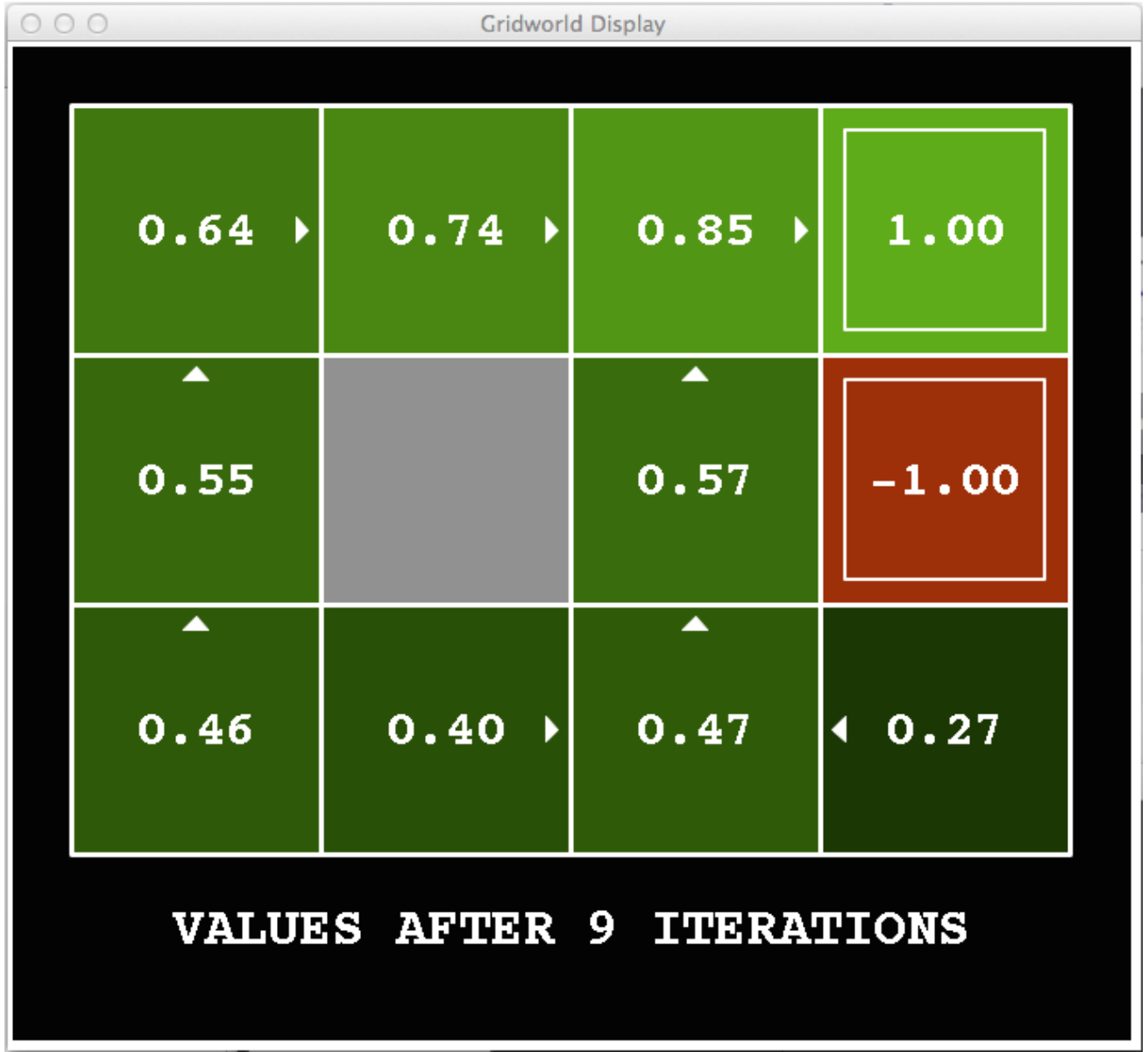
$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$

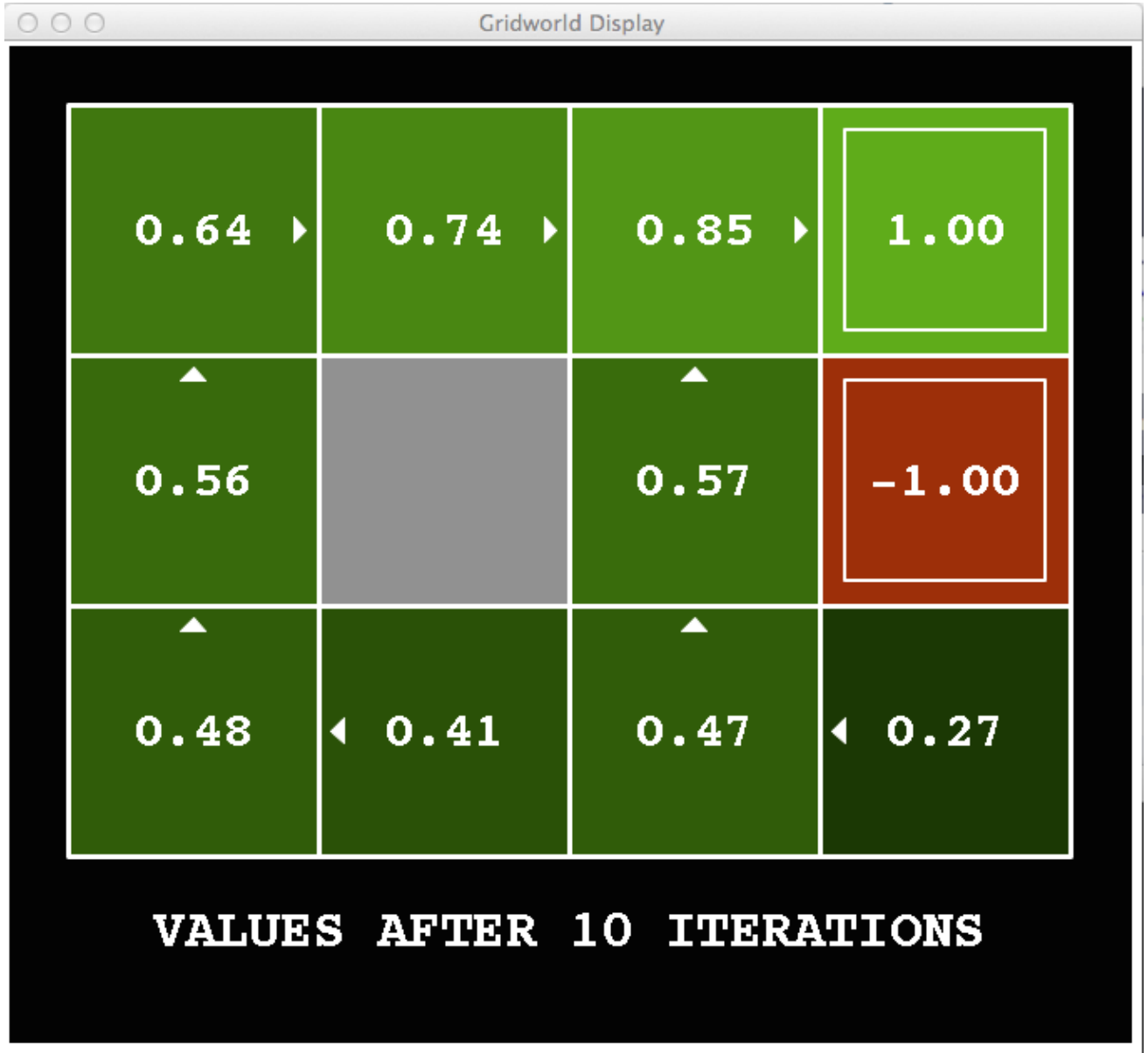
k=9



Noise = 0.2
Discount = 0.9
Living reward = 0

k=10

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

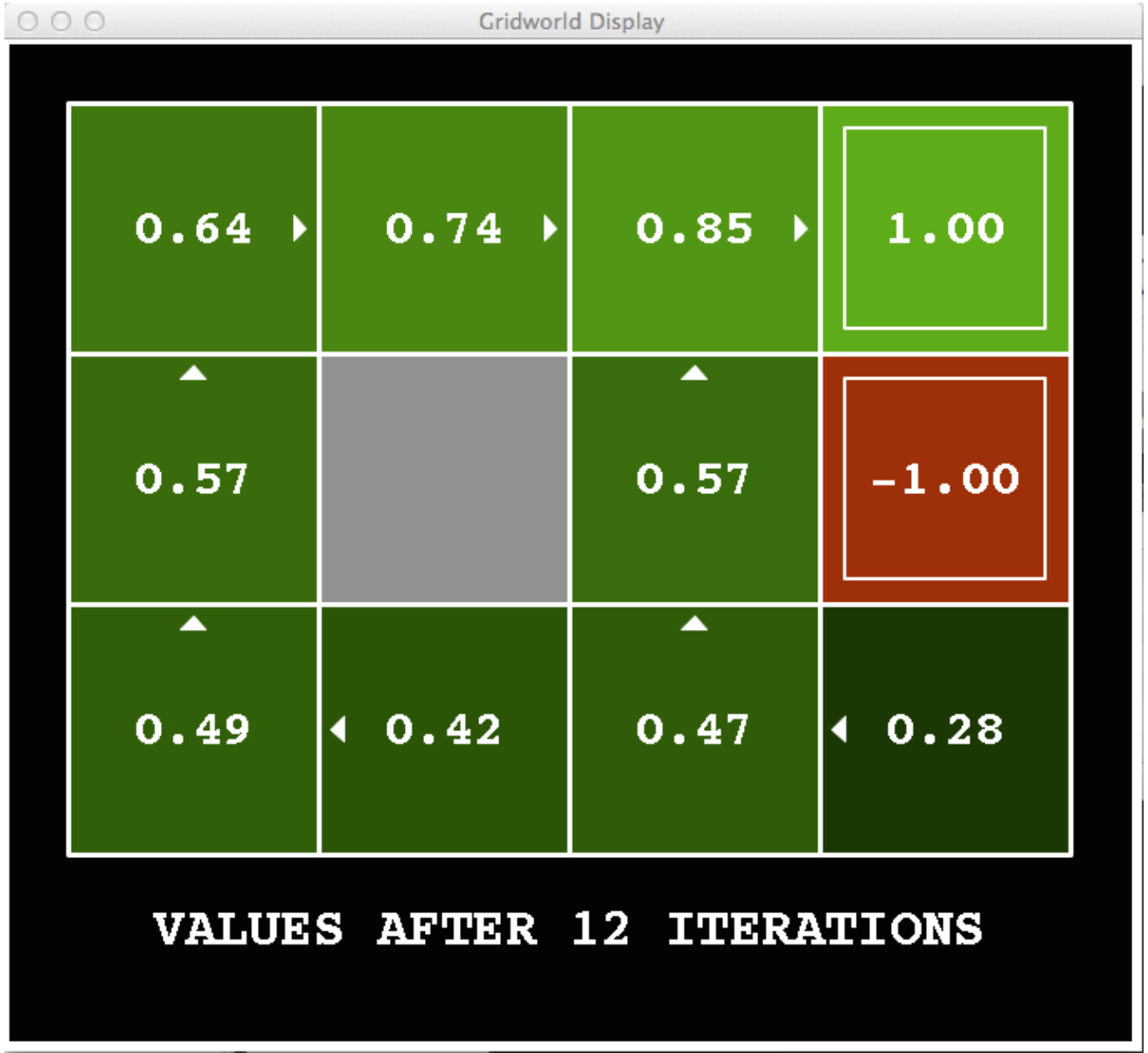
$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$

k=11

Noise = 0.2
Discount = 0.9
Living reward = 0

k=12

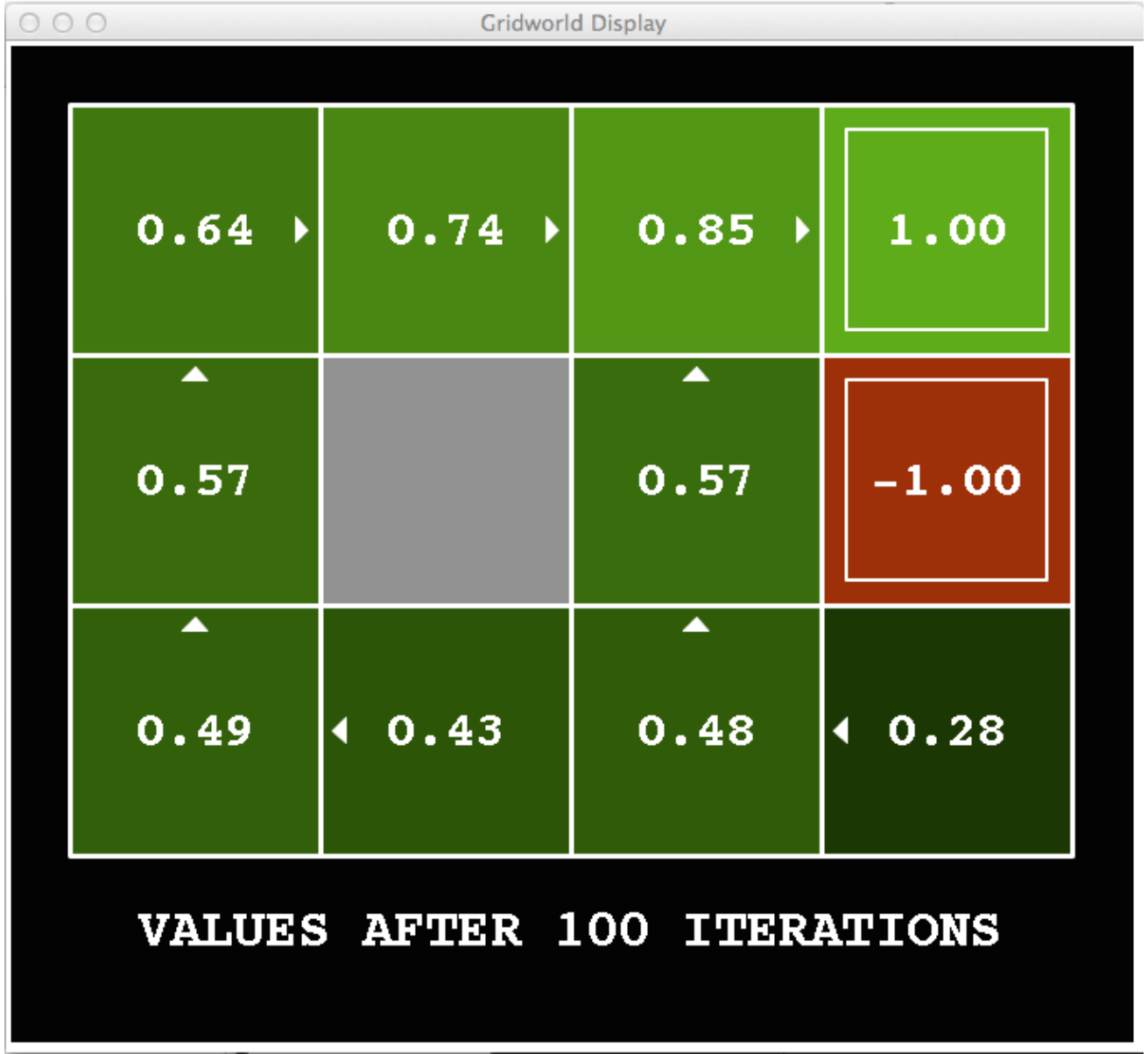
$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

k=100

$$v_{k+1}(s) \doteq \max_a \sum_{s',r} p(s',r|s,a)\left[r+\gamma v_k(s')\right]$$



Noise = 0.2
Discount = 0.9
Living reward = 0

Problems with Value Iteration

- Value iteration repeats the Bellman updates:
- $V_{k+1}(s) \leftarrow \max_a \left[R(s,a) + \sum_{s'} P(s'|s,a)\ \gamma V_k(s')\right]$

$$= \max_a \left[\sum_{s'} P(s'|s,a)\ (R(s,a,s') + \gamma V_k(s'))\right]$$

- Issue 1: It's slow – $O(S^2A)$ per iteration
  - Do we really need to update every state at every iteration?
- Issue 2: A policy cannot be easily extracted
  - Policy extraction requires another $O(S^2A)$
- Issue 3: The policy often converges long before the values
  - Can we identify when the policy converged?
- Issue 4: requires knowing the model, $P(s'|s,a)$, and the reward function, $R(s,a)$
- Issue 5: requires discrete (finite) set of actions
- Issue 6: infeasible in large state spaces

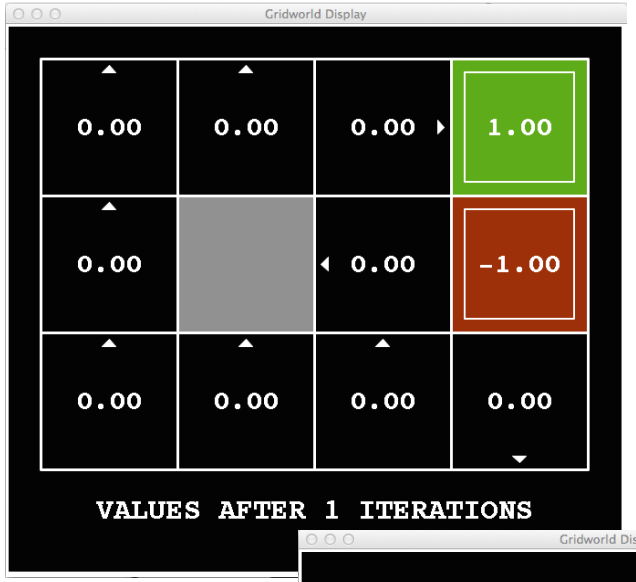
Solutions (briefly, more later...)

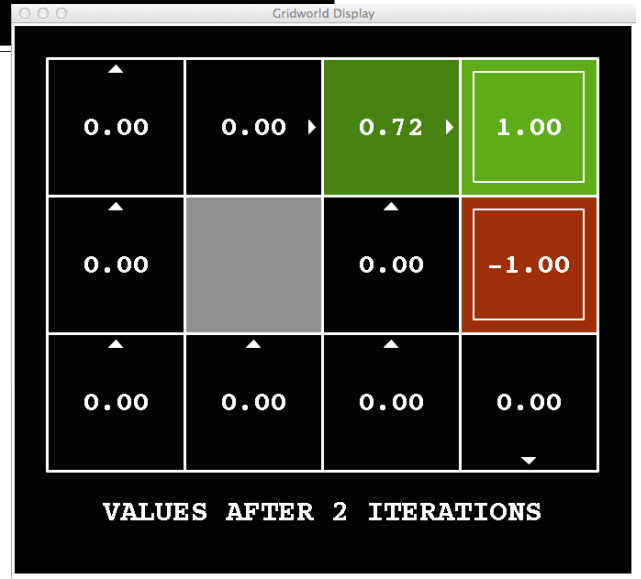
- Issue 1: It's slow – $O(S^2A)$ per iteration
  - Asynchronous value iteration
- Issue 2: A policy cannot be easily extracted
  - Learn q (action) values
- Issue 3: The policy often converges long before the values
  - Policy-based methods
- Issue 4: requires knowing the model and the reward function
  - Reinforcement learning
- Issue 5: requires discrete (finite) set of actions
  - Policy gradient methods
- Issue 6: infeasible for large (or continues) state spaces
  - Function approximators

Issue 1: It's slow – $O(S^2A)$ per iteration

- Asynchronous value iteration
- In value iteration, we update every state in each iteration
- Actually, *any* sequences of Bellman updates will converge if every state is visited infinitely often regardless of the visitation order
- Idea: prioritize states whose value we expect to change significantly

Asynchronous Value Iteration





- Which states should be prioritized for an upda

A single update per iteration

Algorithm 3 Prioritized Value Iteration

1: **repeat**
2: $s \leftarrow \arg\max_{\xi \in S} H(\xi)$
3: $V(s) \leftarrow \max_{a \in A} \{R(s,a) + \gamma \sum_{s' \in S} Pr(s'|s,a) V(s')\}$
4: **for all** $s' \in SDS(s)$ **do**
5: // recompute $H(s')$
6: **end for**
7: **until** convergence

$$SDS(s) = \{s' : \exists a, p(s|s',a) > 0\}$$

For the home assignment set:

$$H(s') = \left| V(s') - \max_a \left\{ R(s',a) + \gamma \sum_{s''} \Pr(s''|s',a) V(s'') \right\} \right|$$

States: A, B, C, T (terminal)

Discount: $\gamma = 0.9$

Actions available in A, B, C: Left and Right (just names)

Terminal: $V(T) = 0$

Transition + Reward model

I'll write it as: from state, action → next state (prob), reward.

From A

- Right: to B with prob 1, reward 0
- Left: to T with prob 1, reward $+1$

From B

- Right: to C with prob 1, reward 0
- Left: to A with prob 1, reward 0

From C

- Right: to T with prob 1, reward $+2$
- Left: to B with prob 1, reward 0

Initial values:

$$V(A) = 0,\ V(B) = 0,\ V(C) = 0,\ V(T) = 0$$

1) Compute SDS sets

Slide definition:

$$SDS(s) = \{s' : \exists a,\ P(s \mid s', a) > 0\}$$

Meaning: states that can transition INTO s (predecessors).

Predecessors for each state

- Who can go into A?
  - From B, action Left → A

  So:

$$SDS(A) = \{B\}$$

- Who can go into B?
  - From A, action Right → B
  - From C, action Left → B

  So:

$$SDS(B) = \{A, C\}$$

- Who can go into C?
  - From B, action Right → C

  So:

$$SDS(C) = \{B\}$$

- Who can go into T?
  - From A, action Left → T
  - From C, action Right → T

  So:

$$SDS(T) = \{A, C\}$$

That's SDS.

2) Compute $H(s)$ values (priority)

Slide uses (essential idea):

$$H(s) = \left| V(s) - \max_a \sum_{s'} P(s'|s,a)\,(R(s,a,s') + \gamma V(s')) \right|$$

So:

- Compute Bellman backup $Backup(s)$
- Then $H(s) = |V(s) - Backup(s)|$

Step A: Compute backups using current $V = 0$

For state A

- Right: $Q(A, \text{Right}) = 0 + 0.9V(B) = 0$
- Left: $Q(A, \text{Left}) = 1 + 0.9V(T) = 1$

So:

$$Backup(A) = \max(0, 1) = 1$$

$$H(A) = |V(A) - Backup(A)| = |0 - 1| = 1$$

For state B

- Right: $0 + 0.9V(C) = 0$
- Left: $0 + 0.9V(A) = 0$

So:

$$Backup(B) = 0, \quad H(B) = |0 - 0| = 0$$

For state C

- Right: $2 + 0.9V(T) = 2$
- Left: $0 + 0.9V(B) = 0$

So:

$$Backup(C) = 2, \quad H(C) = |0 - 2| = 2$$

For terminal T

Usually terminal not updated (fixed), so ignore or treat $H(T) = 0$.

Priority order (largest H first)

$$H(C) = 2 \;>\; H(A) = 1 \;>\; H(B) = 0$$

So prioritized value iteration will update C first.

3) "One update per iteration" + updating predecessors using SDS

Iteration 1: Update state C

Set:

$$V(C) \leftarrow Backup(C) = 2$$

Now we recompute priorities of predecessors of C:

$$SDS(C) = \{B\}$$

So recompute $H(B)$ using new $V(C) = 2$.

Recompute backup for B

- Right: $0 + 0.9V(C) = 0.9 \times 2 = 1.8$
- Left: $0 + 0.9V(A) = 0$

So:

$$Backup(B) = 1.8$$

Current $V(B) = 0$, so:

$$H(B) = |0 - 1.8| = 1.8$$

Now priorities become:

- $H(B) = 1.8$
- $H(A) = 1$

Iteration 2: Update state B

$$V(B) \leftarrow 1.8$$

Recompute predecessors of B:

$$SDS(B) = \{A, C\}$$

Recompute $H(A)$ (and $H(C)$ if needed).

Recompute backup for A (with updated $V(B) = 1.8$)

- Right: $0 + 0.9V(B) = 0.9 \times 1.8 = 1.62$
- Left: $1 + 0.9V(T) = 1$

So:

$$Backup(A) = \max(1.62, 1) = 1.62$$

Current $V(A) = 0$, so:

$$H(A) = |0 - 1.62| = 1.62$$

So next update would be A.

Final snapshot after 2 prioritized updates

$$V(C) = 2, \quad V(B) = 1.8, \quad V(A) = 0 \text{ (not yet updated)}$$

Double the work?

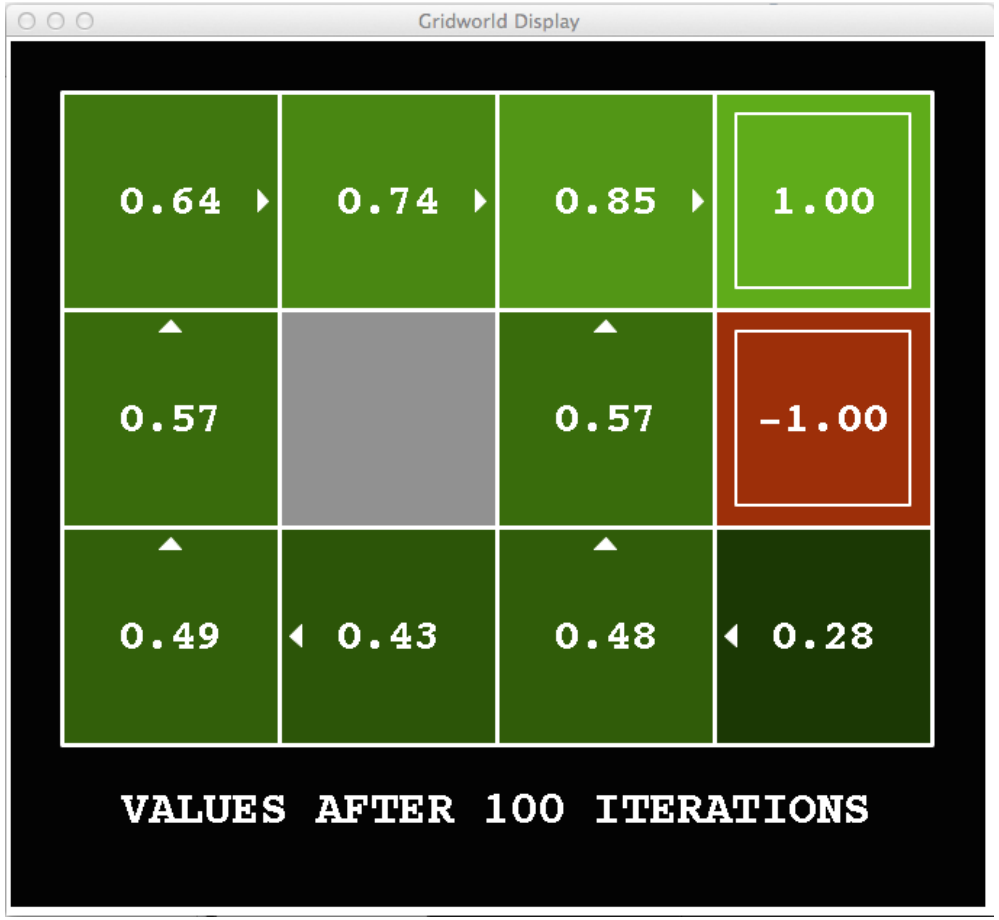
For the home assignment set:

$$H(s') = \left| V(s') - \max_a \left\{ R(s', a) + \gamma \sum_{s''} \Pr(s''|s', a) V(s'') \right\} \right|$$

- Computing priority is similar to updating the state value (W.R.T computational effort)
- Why do double work?
  - If we computed the priority, we can go ahead and update the value for free
- Notice that we don't need to update the priorities for the entire state space
- For many of the states the priority doesn't change following an updated value for a single state s
- Only states s' with $\sum_a p(s'|s, a) > 0$ require update

Issue 2: A policy cannot be easily extracted

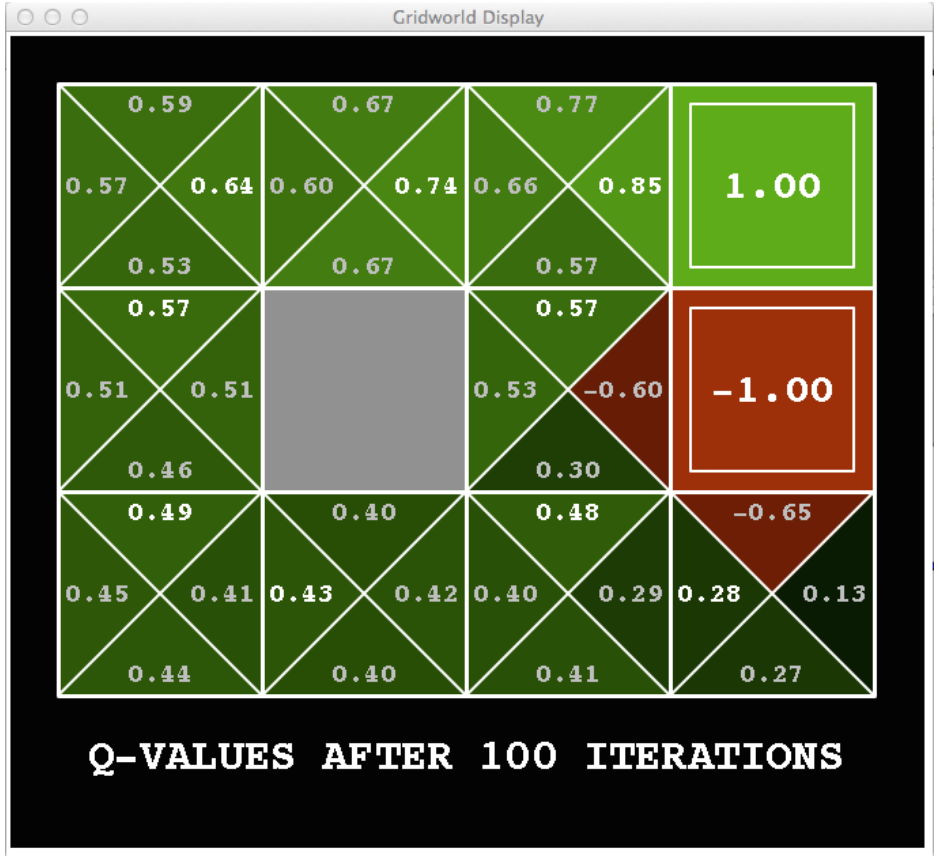
- Given state values, what is the appropriate policy?
  - $\pi(s) \leftarrow \underset{a}{\text{argmax}}\left[R(s,a) + \sum_{s'} P(s'|s,a)\ \gamma V_k(s')\right]$
  - Requires another full value sweep: $O(S^2A)$
- Learn q (action) values instead
- $Q^*(s,a)$ - the expected sum of rewards from being at s, taking action a and then following π^*



End of class #4

Q-learning

- $Q^*(s, a)$ - the expected sum of rewards from being at s, taking action a and then following π^*
- $\pi^*(s) \leftarrow \underset{a}{\text{argmax}}[Q^*(s, a)]$
- Can we learn Q values with dynamic programming?
  - Yes, similar to value iteration



Q-learning as value iteration

-
- $V^*(s) := \max_a [\sum_{s'} P(s'|s,a)\,(R(s,a,s') + \gamma V^*(s'))]$
- $V^*(s) := \max_a [Q^*(s,a)]$
- $Q^*(s,a) := \sum_{s'} P(s'|s,a)\,(R(s,a,s') + \gamma V^*(s'))$
- $Q^*(s,a) = \sum_{s'} P(s'|s,a)\,(R(s,a,s') + \gamma \max_a [Q^*(s',a)])$
- Solve iteratively
  - $Q_{k+1}(s,a) = \sum_{s'} P(s'|s,a)\,(R(s,a,s') + \gamma \max_a [Q_k(s',a)])$
  - Can also use Asynchronous learning

Numerical MDP (small + includes probabilities)

States: A, B, T (terminal)

Actions: L, R available in A and B

Discount: $\gamma = 0.9$

Initialize: $Q_0(s, a) = 0$ for all (s, a)

Terminal: $\max_{a'} Q_k(T, a') = 0$

Transition + reward model

From A:

- Action L: goes to T with prob 1, reward $+1$
- Action R:
  - to B with prob 0.8, reward 0
  - to T with prob 0.2, reward 0

From B:

- Action R: goes to T with prob 1, reward $+2$
- Action L: goes to A with prob 1, reward 0

Iteration 1: Compute Q_1 from $Q_0 = 0$

First note:

$$\max_{a'} Q_0(A, a') = 0, \quad \max_{a'} Q_0(B, a') = 0, \quad \max_{a'} Q_0(T, a') = 0$$

$Q_1(A, L)$

$$Q_1(A, L) = 1 \cdot (1 + 0.9 \cdot 0) = 1$$

$Q_1(A, R)$

$$Q_1(A, R) = 0.8(0 + 0.9 \cdot 0) + 0.2(0 + 0.9 \cdot 0) = 0$$

$Q_1(B, R)$

$$Q_1(B, R) = 1 \cdot (2 + 0.9 \cdot 0) = 2$$

$Q_1(B, L)$

$$Q_1(B, L) = 1 \cdot (0 + 0.9 \cdot 0) = 0$$

✅ So after Iteration 1:

- $Q_1(A, L) = 1$, $Q_1(A, R) = 0$
- $Q_1(B, R) = 2$, $Q_1(B, L) = 0$

Iteration 2: Compute Q_2 using Q_1

Compute needed maxima:

$$\max_{a'} Q_1(A, a') = \max(1, 0) = 1$$

$$\max_{a'} Q_1(B, a') = \max(2, 0) = 2$$

$$\max_{a'} Q_1(T, a') = 0$$

$Q_2(A, L)$

$$Q_2(A, L) = 1 \cdot (1 + 0.9 \cdot 0) = 1$$

$Q_2(A, R)$

$$Q_2(A, R) = 0.8(0 + 0.9 \max Q_1(B)) + 0.2(0 + 0.9 \max Q_1(T))$$

$$= 0.8(0.9 \times 2) + 0.2(0) = 0.8(1.8) = 1.44$$

$Q_2(B, R)$

$$Q_2(B, R) = 1 \cdot (2 + 0.9 \cdot 0) = 2$$

$Q_2(B, L)$

$$Q_2(B, L) = 1 \cdot (0 + 0.9 \max Q_1(A)) = 0.9 \times 1 = 0.9$$

✅ So after Iteration 2:

- $Q_2(A, L) = 1,\ Q_2(A, R) = 1.44$
- $Q_2(B, R) = 2,\ Q_2(B, L) = 0.9$

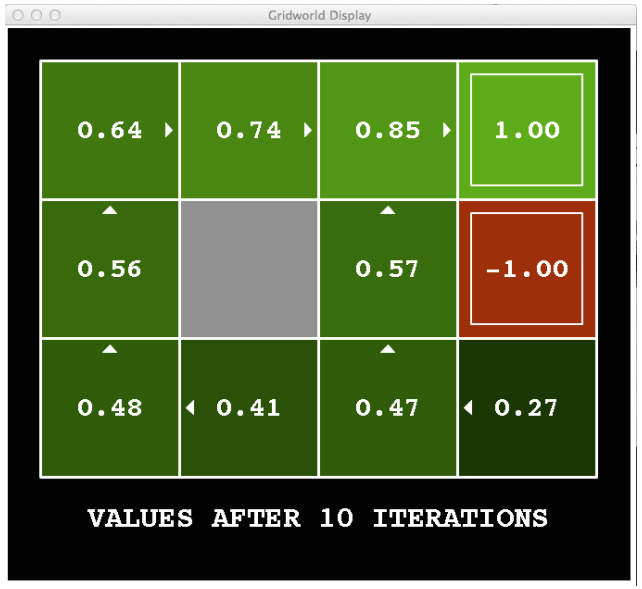
Greedy policy after Iteration 2

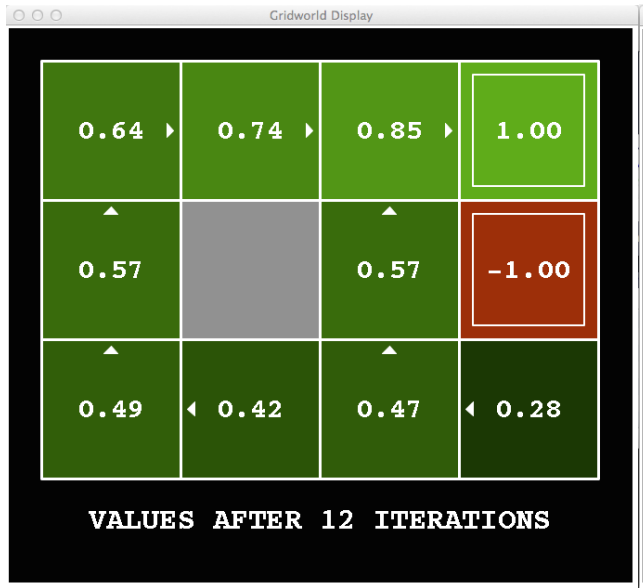
Pick action with larger Q in each state:

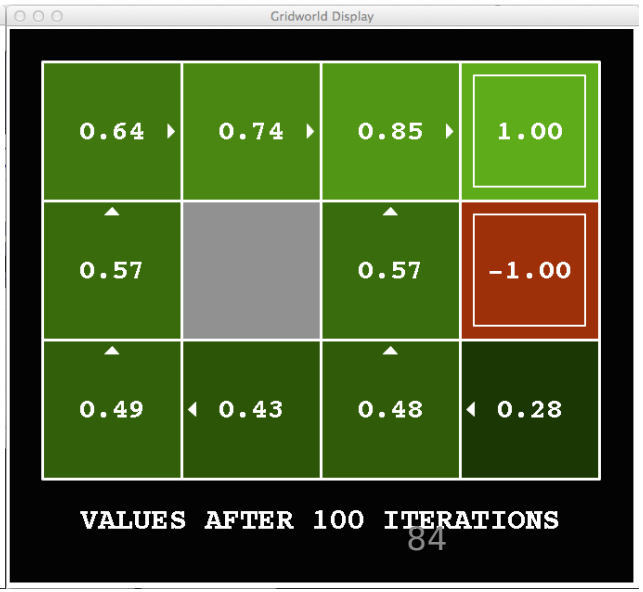
- At A: R (since $1.44 > 1$)
- At B: R (since $2 > 0.9$)

Issue 3: The policy often converges long before the values

- Value iteration converges to the true utility value: $V_{k\to\infty} \to V^*$
- V^* implies the optimal policy: π^*
- Can we converge directly on π^*?
  - Improve the policy in iteration until reaching the optimal one



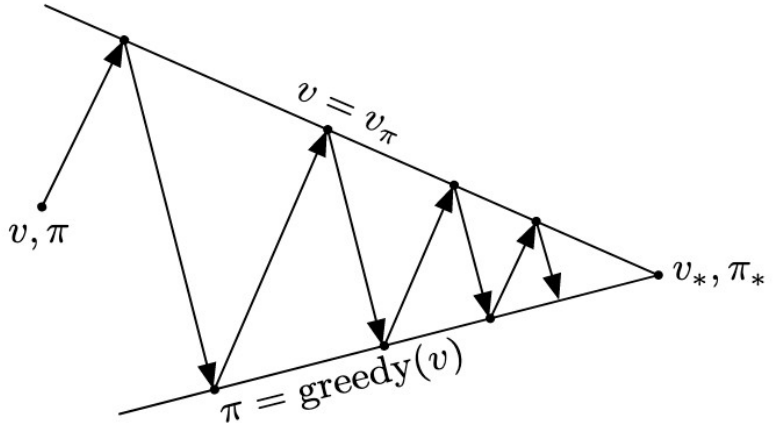




Policy Iteration

1. Compute V_π: calculate state value for some fixed policy (not necessarily the optimal values, $V_\pi \neq V^*$)
2. Update π: update policy using one-step look-ahead with the resulting (non optimal) values
3. Repeat until policy converges

   (optimal values and policy)



- Guaranteed converges to π^*
  - $\forall s, V_{k>0}(s) \leq V_{k+1}(s)$ i.e., π_i improves monotonically with i
  - A fixed point, $\forall s, V_k(s) = V_{k+1}(s)$, implies π^*

Policy Evaluation

- Why is calculating V_π easier that calculating V^*?
  - Turns non-linear Bellman equations into linear equations
- $v^*(s) = \max_a [\sum_{s'} P(s'|s,a)\,(R(s,a,s') + \gamma v^*(s'))]$
- $v_\pi(s) = \sum_{s'} P(s'|s,\pi(s))\,(R(s,\pi(s),s') + \gamma v^*(s'))$
- Solve a set of linear equations in $O(S^2)$
  - Solve with Numpy (numpy.linalg.solve)
  - Required for your home assignment
  - See: https://numpy.org/doc/stable/reference/generated/numpy.linalg.solve.html#numpy.linalg.solve

Question 2 (8 Marks): Policy Evaluation with Probabilistic Transitions (Grid-like)

Consider states $S = \{S_1, S_2, S_3\}$ and terminal T with $V(T) = 0$. Discount $\gamma = 0.8$.

A fixed policy π produces these transition and reward dynamics:

- From S_1:
  - to S_2 with prob 0.7, reward $+2$
  - to S_3 with prob 0.3, reward 0
- From S_2:
  - to S_2 with prob 0.6, reward $+1$
  - to T with prob 0.4, reward $+4$
- From S_3:
  - to S_1 with prob 1.0, reward -1

Find $V_\pi(S_1), V_\pi(S_2), V_\pi(S_3)$.

Solution

Write Bellman expectation equations:

For S_1

$$V_1 = 0.7(2 + 0.8V_2) + 0.3(0 + 0.8V_3)$$

$$V_1 = 1.4 + 0.56V_2 + 0.24V_3$$

For S_2

$$V_2 = 0.6(1 + 0.8V_2) + 0.4(4 + 0.8V_T)$$

Since $V_T = 0$:

$$V_2 = 0.6 + 0.48V_2 + 1.6$$

$$V_2 = 2.2 + 0.48V_2$$

$$V_2 - 0.48V_2 = 2.2 \Rightarrow 0.52V_2 = 2.2 \Rightarrow V_2 = \frac{2.2}{0.52} = 4.2308$$

For S_3

$$V_3 = -1 + 0.8V_1$$

Now substitute V_3 into V_1:

$$V_1 = 1.4 + 0.56(4.2308) + 0.24(-1 + 0.8V_1)$$

Compute step-by-step:

- $0.56 \times 4.2308 = 2.3692$

  So:

$$V_1 = 1.4 + 2.3692 + 0.24(-1) + 0.24(0.8V_1)$$

$$V_1 = 3.7692 - 0.24 + 0.192V_1$$

$$V_1 = 3.5292 + 0.192V_1$$

$$V_1 - 0.192V_1 = 3.5292 \Rightarrow 0.808V_1 = 3.5292 \Rightarrow V_1 = \frac{3.5292}{0.808} = 4.3683$$

Now:

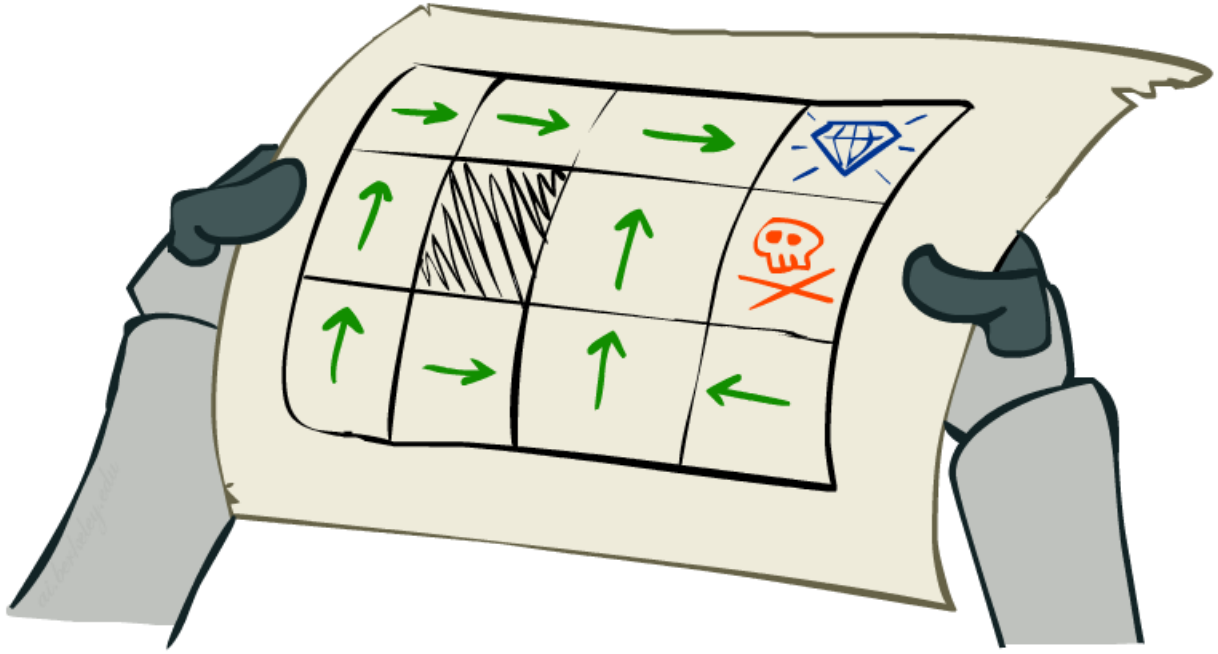
$$V_3 = -1 + 0.8(4.3683) = -1 + 3.4946 = 2.4946$$

✅ Final (approx):

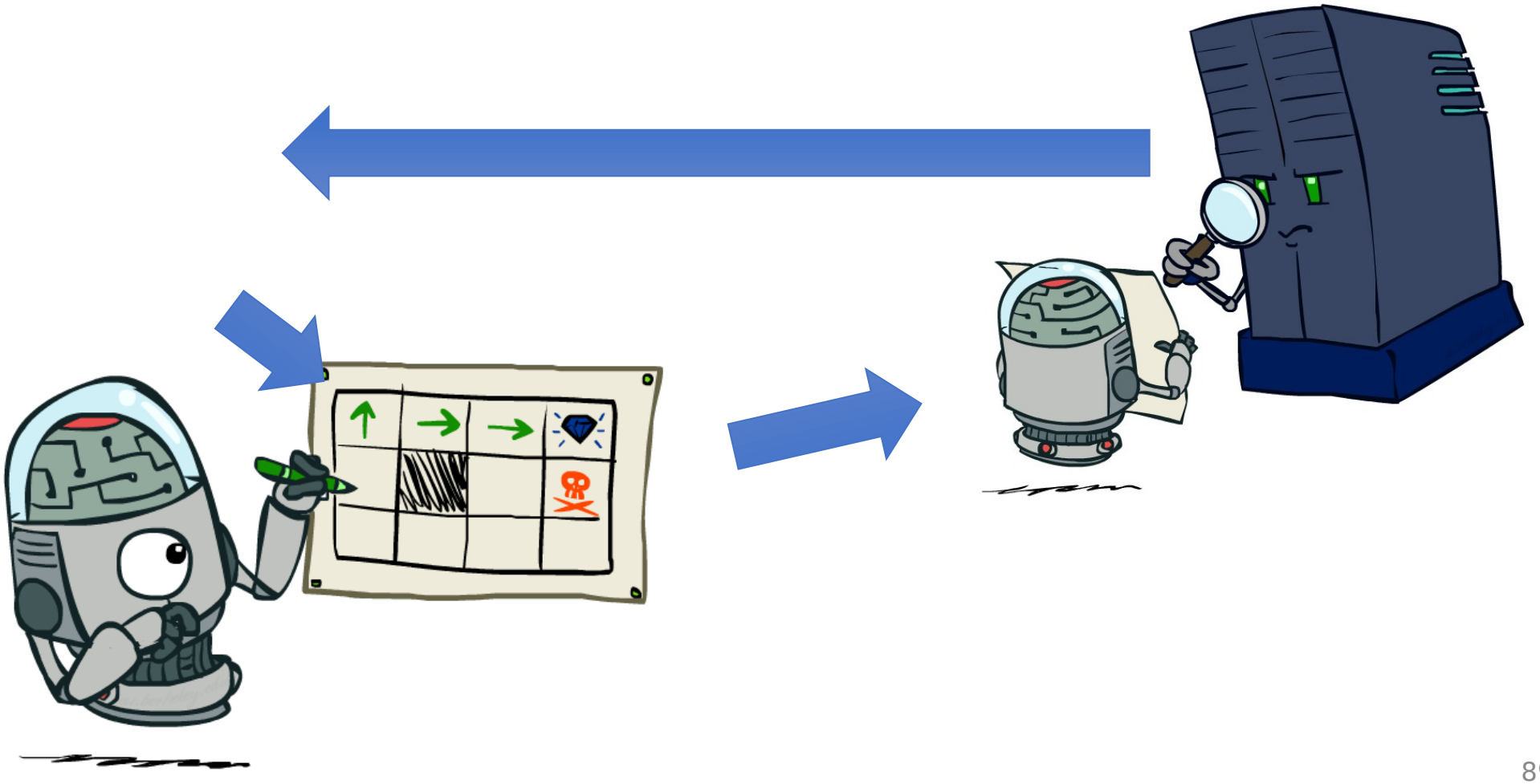
- $V_\pi(S_1) = 4.368$
- $V_\pi(S_2) = 4.231$
- $V_\pi(S_3) = 2.495$

Policy value as a Linear program

- $v_{11} = 0.8 \cdot (-0.1 + 0.95 \cdot v_{12}) + 0.1 \cdot (-0.1 + 0.95 \cdot v_{21}) + 0.1 \cdot (-0.1 + 0.95 \cdot v_{11})$
- $v_{12} = 0.8 \cdot (-0.1 + 0.95 \cdot v_{13}) + 0.2 \cdot (-0.1 + 0.95 \cdot v_{12})$
- …
- $v_{42} = -1$
- $v_{43} = 1$



Policy iteration

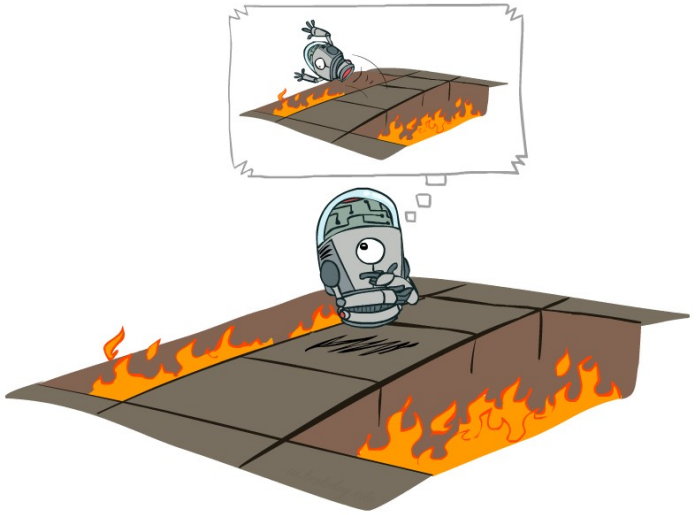


Comparison

- Both value iteration and policy iteration compute the same thing (optimal state values)
- In value iteration:
  - Every iteration updates both the values and (implicitly) the policy
  - We don’t track the policy, but taking the max over actions implicitly define it
- In policy iteration:
  - We do several passes that update utilities with fixed policies (each pass is fast because we consider only one action, not all of them)
  - After the policy is evaluated, a new policy is chosen (slow like a value iteration pass)
  - The new policy will be better (or we’re done)

Issue 4: requires knowing the model and the reward function

- We will explore online learning (reinforcement learning) approaches
- How can we learn the model and reward function from interactions?
- Do we even need to learn them? Can we learn V^*, Q^* without a model?
- Can we do without V^*, Q^* ? Can we run policy iteration without a model?



Offline

Online

Issue 5: requires discrete (finite) set of actions

- We will explore policy gradient approaches that are suitable for continuous actions, e.g., throttle and steering for a vehicle
- Can such approaches be relevant for discrete action spaces?
  - Yes! We can always define a continues action space as a distribution over the discreate actions (e.g., using the softmax function)
- Can we combine value-based approaches and policy gradient approaches and get the best of both?
  - Yes! Actor-critic methods

Issue 6: infeasible in large (or continues) state spaces

- Most real-life problems contain very large state spaces (practically infinite)
- It is infeasible to learn and store a value for every state
- Moreover, doing so is not useful as the chance of encountering a state more than once is very small
- We will learn to generalize our learning to apply to unseen states
- We will use value function approximators that can generalize the acquired knowledge and provide a value to any state (even if it was not previously seen)

Notation

- π^* - a policy that that yields the maximal expected sum of rewards
- $V^*(s)$ - the expected sum of rewards from being at s then following π^*
- $V_\pi(s)$ - the expected sum of rewards from being at s then following π
- $Q^*(s, a)$ - the expected sum of rewards from being at s, taking action a and then following π^*
- $Q_\pi(s, a)$ - the expected sum of rewards from being at s, taking action a and then following π
- G_t - observed sum of rewards following time t, i.e., $\sum_{k=t}^{T} r_k$

Required Readings

1. Chapter-3,4 of Introduction to Reinforcement Learning,2nd Ed., Sutton & Barto

Thank you